

Understanding Navigational Success in Humans

by
Benjamin Dennis Nelligan

A dissertation submitted to Johns Hopkins University in conformity with the
requirements for the degree of Doctor of Philosophy.

Baltimore, Maryland

December, 2016

Abstract

In our daily lives, we often need to move from one location to another. We move around rooms in our homes, walk through college campuses, and find our way through mazes of city streets. The need to successfully navigate is critical to one's life. But despite this ubiquitous need, how successful we are at navigating varies significantly between individuals. Previous research on this topic has emphasized the information one learns about the environment (e.g. location of landmarks, understanding the structure of the environment, etc.), leading to environmental structure learning being synonymous with successful navigation. But this assumption has never been empirically evaluated. Thus the goal of this project was to understand the extent to which environmental structure learning is, in fact, the similar to successful navigation. The first step in accomplishing this was to develop performance-based measures of navigation that capture variance in both *how* and *how well* one navigates. This was accomplished in Experiments 1 & 2. Using these measures, Experiment 3 demonstrated that good environmental learning is dissociable from successful navigation. Following this, we used what is known about the predictors of good environmental structure learning to understand the factors that contribute to successful navigation. The results indicated that the ability to use novel and familiar solutions and a bias towards using familiar solutions were predictive of an individual's success when navigating. Gender differences were also observed, such that novel solution capacity was the primary contributor of success for males, whereas familiar solution capacity and a bias to use familiar solutions were the largest contributors to success for females. This work elucidates the factors that contribute to successful navigation and shifts the dialogue about navigation from being

about learning the structure of the environment to being about how successful one is when they navigate.

Table of Contents

Abstract	ii
Table of Contents	iv
List of Tables	x
List of Figures	xi
1 Chapter 1: Literature Review	1
1.1 Introduction	1
1.2 Selecting Appropriate Solutions.....	3
1.2.1 Preference and propensity for specific solutions	4
1.2.2 Spontaneous flexibility of solution preference and selection	5
1.2.3 Summary	6
1.3 Capacity for Specific Solutions.....	7
1.3.1 Novel solutions	7
1.3.2 Familiar solutions.....	8
1.3.3 Reversal solutions	9
1.3.4 Summary	10
1.4 Spatial Skills.....	10
1.4.1 Mental rotation.....	11
1.4.2 Spatial perspective taking	12
1.4.3 Spatial working memory.....	13
1.4.4 Summary	14
1.5 Interim Summary.....	15
1.6 Methodological Concerns	16

2 Chapter 2: Development of Relevant Measures	19
2.1 Experiment 1 Introduction	19
2.2 Methods	20
2.2.1 Participants	20
2.2.2 Materials and Procedure	20
2.2.2.1 Dual Solution Paradigm	20
2.2.2.2 Spatial Learning Styles Assessment	22
2.2.2.3 Spatial inventories.....	24
2.2.2.3.1 Santa Barbara Sense of Direction Scale.....	24
2.2.2.3.2 Questionnaire on Spatial Representations	24
2.2.2.3.3 Mental Rotation Test	25
2.2.2.3.3 Spatial Perspective Test	25
2.3 Results	25
2.3.1 Full & Reduced Datasets	26
2.3.2 Summary Data	27
2.3.3 Comparison of Dual Solution Paradigm & Spatial Learning Styles Assessment.....	29
2.3.4 Relationships among Performance-Based Measures, Self-Reports & Spatial Skills	29
2.3.4.1 Successful navigation.....	33
2.3.4.1.1 Self-report measures.	33
2.3.4.1.1.1 Santa Barbara Sense of Direction Scale.....	33
2.3.4.1.1.2 QSR-Style	33

2.3.4.1.2 Mental Rotation Test.....	35
2.3.4.2 Navigational style (Solution Index).	36
2.3.4.2.1 Self-report measures.	36
2.3.4.2.1.1 Santa Barbara Sense of Direction Scale.....	36
2.3.4.2.1.2 QSR-Style	38
2.3.4.2.2 Mental Rotation Test.....	38
2.3.5 The Stability of the SLSA SI (Monte Carlo Simulations)	39
2.3.5.1 Stability of SI	39
2.3.5.2 Stability of Observed Correlation	39
2.4 Discussion	42
2.5 Experiment 2 Introduction	43
2.6 Methods.....	44
2.6.1 Participants	44
2.6.2 Materials and Procedure	44
2.7 Results and Discussion.....	45
2.7.1 Summary Data	45
2.7.2 Success Rate.....	48
2.7.2.1 Self-report measures	48
2.7.2.1.1 Santa Barbara Sense of Direction	48
2.7.2.1.2 QSR-Style	48
2.7.2.2 Mental Rotation Test	48
2.7.3 Solution Index.....	49
2.7.3.1 Self-report measures	49

2.7.3.1.1 Santa Barbara Sense of Direction	49
2.7.3.1.2 QSR-Style	49
2.7.3.2 Mental Rotation Test	49
2.7.4 Comparison of Experiment 1 and Experiment 2.....	50
2.8 Discussion	51
2.8.1 Do Self-Report Measures Correspond with Performance-Based Measures?	51
2.8.2 Validity of the SLSA	52
2.8.3 Spatial Skills and Successful Navigation.....	53
2.8.4 Conclusion	54
3 Chapter 3: Experiment 3	56
3.1 Introduction	56
3.1.1 Selecting appropriate solutions	59
3.1.1.1 Preference and Propensity for Specific Solutions	59
3.1.1.2 Spontaneous flexibility of solution selection	61
3.1.1.3 Summary	62
3.1.2 Capacity for specific solutions	62
3.1.3 Spatial Skills	65
3.1.4 Present Study	68
3.2 Methods	68
3.2.1 Participants	68
3.2.2 Materials	68
3.2.2.1 Spatial Learning Styles Assessment (SLSA)	68

3.2.2.2 Success Rate Assessment.....	70
3.2.2.3 Required Solutions Task.....	71
3.2.2.4 Questionnaire on Spatial Representations	72
3.2.2.5 Mental Rotation Test	72
3.2.2.6 Non-Sequential Corsi Block	73
3.2.3 Timing	74
3.2.4 Task Order	74
3.3 Results	75
3.3.1 Characterization of Performance on New Tasks	75
3.3.1.1 Success Rate Assessment.....	76
3.3.1.2 Required Solutions Task	78
3.3.2 Key Question and Measures	80
3.3.3 Relationships among measures	82
3.3.4 Biases	86
3.3.5 Gender Differences	87
3.3.6 Understanding Unique Contributions to Success	90
3.3.6.1 SI	90
3.3.6.2 Reversals	93
3.3.7 Gender Differences	95
3.3.7.1 Males	97
3.3.7.2 Females	99
3.3.8 Role of Spatial Skills	101
3.3.8.1 Mental Rotation	102

3.3.8.2 Spatial Working Memory	102
3.3.9 Understanding Prioritization of Predictors	103
3.3.9.1 Males	104
3.3.9.2 Females	105
3.3.10 Summary	105
4 Chapter 4: General Discussion.....	106
4.1 Spatial Learning Styles Assessment.....	106
4.2 Are self-reports measuring the same constructs as behavioral measures?	107
4.3 Do spatial skills affect success?	108
4.4 Do aspects of solution selection affect success?	109
4.5 Does capacity for specific solutions affect success?	111
4.6 Is successful navigation the same as good environmental learning?	114
4.7 Does volitional solution use relate to required solutions use?	115
4.8 Conclusions	116
References	118
Biographical Sketch	126

List of Tables

1. Means and standard deviations for all measures	27
2. Correlations (r) among the individual differences test broken down by dataset and gender in Experiment 1	31
3. Correlations (r) between each dependent measure from the navigation tests and each of the individual differences in the full dataset measures broken down by gender in Experiment 1	34
4. Correlations (r) between each dependent measure from the navigation tests and each of the individual differences measures in the reduced dataset broken down by gender in Experiment 1	37
5. Means and standard deviations for all measures in Experiment 2.....	46
6. Correlations (r) among the individual differences test broken down by dataset and gender in Experiment 2.....	47
7. Correlations (r) between each dependent measure from the navigation tests and each of the individual differences measures broken down by dataset and gender in Experiment 2.....	50
8. Correlations between all measures in experiment 3	84
9. Means and standard deviations for all measures in Experiment 3.....	88
10. Simultaneous regressions predicting SRA success rate	91
11. Simultaneous regressions predicting SRA success rate by gender in Experiment 3 ...	99
12. Unstandardized indirect effects of capacity measures mediating the influence of spatial skills on success.....	102
13. Stepwise regressions predicting SRA success rate separately for each gender	104

List of Figures

1. Example diagrams of the Dual Solution Paradigm and Spatial Learning Styles Assessment.....	22
2. Screenshot of SLSA trial from the participant's view	23
3. Histograms of solution index values for DSP and SLSA in experiment 1	28
4. Correlations between behavioral measures of spatial learning success and style	30
5. Histograms of correlations between SI as measured by a 16 trial SLSA and SI as measured by 5-10 trial versions of the SLSA	40
6. Histograms of the correlations between Mental Rotation Test scores and SLSA success rate for all 6 trial subsets of SLSA trials	41
7. Example item from Mental Rotation Test.	73
8. Diagram of the Non-Sequential Corsi Block task.....	74
9. Possible orders of task presentation.....	75
10. Histogram of success rates on the Success Rate Assessment	76
11. Histogram of SRA Solution Indices	77
12. Histogram of novel and familiar solution rates.....	78
13. Histograms of success rates for novel, familiar, and reversal Required Solutions trials	79

Chapter 1: Literature Review

1.1 Introduction

In our everyday lives, we face a plethora of challenges that require us to navigate through the world. We move from room to room in our houses, drive to and from work, and explore and learn the layout of unfamiliar cities. In fact, it is difficult to imagine a day in which one does not need to navigate from one location to another. Most of our efforts to navigate are successful, but this success is not universal. Nearly everyone can think of a time in which they were lost or unable to find a location and had to offload the challenge by turning to GPS or calling a friend for directions. These situations result in everything from anxiety and frustration at not knowing where something is to actual danger from wandering into an unsafe area. Inasmuch as it is important to avoid such issues and arrive on time to a variety of destinations, being able to successfully navigate is critical to one's daily life. Critically though, we are not all equally successful when we navigate. Some people struggle to find their way even in familiar environments, whereas others seem to always find their way to their destination. Given that successful navigation is not universal, we want to know, "what makes some individuals more successful at navigation than others?"

Decades of research have provided us with a wealth of knowledge about how individuals differ in the way they navigate. We know that individuals differ in terms of how they approach the task of navigation (e.g. the solutions they use, the kinds of information they prefer to use, etc.), the information they learn about environments they navigate in (e.g. locations of salient landmarks, distances and directions between locations, etc.), and the spatial abilities that support or contribute to navigation. What is notable about these investigations is that they have implicitly or explicitly focused on what it means to be a good navigator in terms of how much

one seems to know about the structure of an environment. These studies use participants' estimations of distances, estimates of directions to unseen locations, accuracy at map drawing, and other similar measures as proxies for successful navigation without ever directly measuring how often participants get to their goal location. Undoubtedly these are important and interesting matters, but they may be missing the most critical goal of navigation. In our lives, the most important part of how we navigate can be distilled into a simple question - *did you get there?*

If you arrive at your destination, then in terms of a goal, you have navigated successfully. Certainly learning more about the structure of an environment could be quite useful for this. It would not be surprising if people with better explicit knowledge of their environment are better able to navigate through it. But that does not mean that the only way to regularly be successful at navigation is to have a vast and thorough knowledge of the environment around you. Although much of the previous work on individual differences in navigation is based on the idea that good environmental learners will be good navigators, there is no evidence to support reducing successful navigation to one's quantity/quality of environmental learning.

In this manuscript, we seek to understand why some individuals are more successful navigators than others by removing the assumption that the spatial information one learns about an environment is a proxy for their ability to navigate in that environment. Rather, we will ask more directly, "what makes some people get to their goal location more often than others?" To begin to answer this question, we will review what is known about key factors which have been demonstrated to relate to navigation and environmental learning.

1.2 Selecting Appropriate Solutions

By shifting the discussion from good environmental learning to successful navigation, we lay open the possibility that there are multiple ways to be successful. This emphasis on multiple kinds of solutions to navigation allows for new possibilities as to what may contribute to someone navigating successfully. In any given situation, a person can be characterized as using a particular kind of solution to get to their destination. Critically though, individuals seem to use different kinds of solutions at different rates. Some individuals tend to almost always use the same kinds of solutions, whereas others tend to use a relatively balanced mix of different solutions. More specifically, when navigating in virtual environments, individuals vary in the mixture of solutions they use – in fact individuals fall at all points of a continuum of the relative use of previously navigated familiar paths (that one knows will be successful) and novel paths that had to be reasoned out (Furman, Clements-Stephens, Marchette, & Shelton, 2014; Marchette, Bakker, & Shelton, 2010; for review, see Shelton, Marchette, & Furman, 2013).

Given the variability in the selection of solutions, it could be the case, that individual differences in how or which solutions are selected contribute to how successful an individual ultimately is when navigating. For example, it could be that some kinds of solutions more often lead to success than others, and thus selecting those solutions leads to one getting to their destination more often. More likely, individuals who can correctly adjudicate among possible solutions might be more successful than those that stick to one or another (e.g., Shelton, unpublished preliminary data), but the relationship between solution use and success rate has yet to be systematically examined. There are three different ways to think about solution use that might have different contributions to successful navigation: the strength of subjective preference

for different solutions, the behavioral bias for using different solutions, and the propensity to use a variety of solutions when navigating.

1.2.1 Preference and propensity for specific solutions. There are different kinds of solutions to navigation problems and individuals differ in their reported preference or lack thereof for each kind of solution (e.g. Pazzaglia & DeBeni, 2001). There is some evidence that connects a preference for learning the global structure of an environment, which underlies the ability to identify correct novel pathways, to navigation performance. Self-reported preference for this kind of learning is positively correlated with self-reported “sense of direction”, or how good one thinks they are when navigating (Prestopnik & Roskos-Ewoldsen, 2000), and “sense of direction” is, in turn, predictive of knowledge of distances and directions in an environment (Hegarty et al., 2002). In the other direction, lower preference for global structure information is associated with more anxiety in situations that require navigating, and this anxiety is negatively associated with measures of distance and direction estimation (Lawton, 1994). These results provide indirect and/or inconclusive evidence that preferences for global structure information, which is required for executing solutions, predict better environmental learning and thus, to the extent to which environmental learning is predictive of successful navigation, we might expect that these preferences are also predictive of successful navigation.

It is important to note that, as a field, we are still elucidating the extent to which these self-reports reflect behavior. For example, there are countless examples of processes that are implicit in nature (e.g. Greenwald, McGhee, & Schwartz, 1998; Milner, Corkin, & Teuber, 1968; Nisbett & Wilson, 1977; Schacter, 1987; Squire, 1992). If such non-declarative processes contribute to navigation, then self-reports are unlikely to accurately or completely capture these aspects of behavior. One study has found that self-reported preferences correlated with behavior

in a virtual navigation task (Furman et al., 2014), but this finding needs to be replicated in order to draw a definite conclusion. Given that observed biases and self-reported preferences may pick up on different constructs, both will be investigated here. In summary, self-reported preference for global structure information has been indirectly related to how well an individual understands the spatial relationships between objects in an environment and there is preliminary evidence that these self-reported preferences may be indicative of observed behavior. Thus we will measure both self-reported preferences and behavioral biases and predict that both preferences and biases for global structure information will be related to successful navigation in this study.

1.2.2 Spontaneous flexibility of solution preference and selection. The preceding section is heavily driven by the idea that, at least for a given individual, one solution might be better or worse than another. However, it is possible that one's preference for a specific kind of solution is not critical to success. Instead, it may be the extent to which one is capable of switching among solutions in different situations. The (indirect) evidence presented above indicates that a self-reported preference for one kind of solution may confer an advantage in some navigationally-relevant tasks. This could be because individuals who self-report a preference for global structure information are *able* to use novel solutions in some situations in addition to other kinds of solutions, which might reflect having more potential solutions available when selecting what will work for a given situation. In this way, it may not be the preference itself that contributes to success, but the ability to use a variety of solutions in any given situation.

We might also expect that, irrespective of reported preference or observed bias, the ability to shift solutions in response to different navigational challenges might be a better predictor of success than any aspect of reported preference. For the sake of brevity, we will refer

to this ability to switch solutions as flexibility in solution use. This predicts two possible scenarios for how solution selection might be related to success. First, as described above, it may be that preference for more global structure information is indicative of better flexibility in solution use. In such a case, preference and measures of flexibility in solution use will predict success, but will not have independent contributions to it. Alternatively, it may be that flexibility in solution use is independent of reported preferences (which may or may not tell us anything about what people *can* do). If so, then we would expect a greater contribution of flexibility in solution use to predicting success.

1.2.3 Summary. The shift from focusing on environmental learning to focusing on successful navigation opens the possibility that the kinds of solutions one uses may influence whether they get to their destination. Previous research has related self-reported preference for global structure information, which is necessary for successfully using novel paths, to better environmental learning and indirectly to successful navigation. To the extent that good environmental learning is indicative of successful navigation, we would expect to find that measures of preference and bias for learning global structure are predictive of successful navigation. Not finding this would indicate that, at the least, preferences and biases indicative of good environmental learning are not necessary to be successful and that other kinds of solutions, such as relying on familiar paths, may be just as effective.

Another possibility is that being able to use multiple solutions in any given situation may confer an advantage when navigating and that spontaneously using a variety of different solutions when navigating is indicative of this ability. If this is the case, we would expect to find that measures of flexibility in solution use predict success. Not finding this would be consistent

with views that one kind of solution is better suited to success than others or that it is one's capacity to use particular kinds of solutions that best predicts success.

1.3 Capacity for Specific Solutions

As discussed earlier, in most real-world situations that require navigation, there is more than one way a person can go and still make it to their destination. We have already discussed one critical aspect of this as it related to successful navigation – selecting an appropriate solution. But there might be more contributions to success than just which solution you use. How well one uses different kinds of solutions may also influence one's overall success. For example, if someone were perfectly able to select an ideal solution every time they navigated, but he had little to no aptitude for executing some of those solutions, he would not likely be successful every time. In line with previous theories that learning the global structure of an environment is critical to navigating well, it could also be the case that one's capacity for solutions which require such knowledge is most predictive of success.

Previous research has identified three categories of solutions to describe the different ways one can go in situations in which one has had some first-hand experience with the environment: novel solutions, familiar solutions, and reversal solutions, with the first two most commonly used and most thoroughly researched solutions (e.g. Furman et al., 2014; Marchette et al., 2010). Much of the previous work on these solutions has focused on an individual's subjective preference or bias for different solutions rather than one's ability to use a specific kind of solution. This evidence is reviewed below. But, we do not yet have a strong understanding of how the capacity to use these different solutions related to one's preference or bias to use them.

1.3.1 Novel solutions. Novel solutions involve identifying a previously untraveled path using one's knowledge of the environment. For example, if there was construction on some of

the streets you usually use to drive home from work, you could use your knowledge of the neighborhood to find a detour, even if you have never driven that exact route before. Novel paths do not need to be shortcuts though. For example, a person may need to walk across campus to meet with a colleague in another building. But along the way, that person realizes they are going to be too early and decides to take a longer, more circuitous path. The key feature of a novel solution is that the individual is not familiar with that particular path and thus the individual needs to use their knowledge about the structure of the environment to reason about the solution.

There is some evidence that connects a preference for learning the global structure of an environment, which underlies the ability to identify correct novel pathways, to navigation performance. Briefly, stronger self-reported preference for global structure information has also been related to self-reported “sense of direction” (Prestopnik & Roskos-Ewoldsen, 2000), and less anxiety about navigating (Lawton, 1994), both of which are indicative of better environmental learning. At present, the most we can say is that one’s self-reported *preference* for global structure information, relates indirectly to constructs which may be predictive of successful navigation. Given the logical argument that capacities for solutions may be critical to success when navigating, this remains an important area for investigation.

1.3.2 Familiar solutions. Familiar solutions involve retracing a previously navigated path. The most common example of this is when a person takes the same path to go home from work every day. After some exposure to the path, one no longer needs to reason about where they are in space or where they need to go, that person is able to simply follow the series of navigational events they have followed in the past. This has been proposed to be similar in nature to stimulus-response learning (e.g. Schwabe et al., 2008). These solutions are not as flexible as

novel solutions in that a disruption to the series of events, such as a blocked road, can completely disrupt the solution. But because one is not reasoning about spatial relations, it is also less cognitively effortful. For example, it is common for people to think about things or have conversations with others when they are driving their usual route home from work, but the same activities become very disruptive when one is driving through an unfamiliar cities downtown area, which requires reasoning about the environment.

Preference for familiar solutions has been previously investigated, but unlike preference for novel solutions, the relationships with other constructs were sparse at best. No relationships were found with sense of direction (Prestopnik & Roskos-Ewoldsen, 2000), spatial anxiety (Lawton, 1994), or success at virtual navigation tasks (Furman et al., 2014). This could be, at least in part, because these kinds of solutions or the processes supporting them are relatively more non-declarative than novel solutions, and thus the self-reports used to measure these preferences are not capable of accurately measuring preference. Although there is no connection between preference for familiar solutions and navigation, the possibility remains that how proficient someone is at these kinds of solutions may relate to their overall success when navigating.

1.3.3 Reversal solutions. Reversal solutions involve using a familiar solution, but in the opposite direction of how it was originally experienced. This is distinct from a familiar solution because a person isn't able to use the same sequence of events to retrace their path. It is distinct from novel solutions because the person has had some experience with the path before using it. Relative to novel and familiar solutions, much less is known about reversal solutions. One study found that participants who were good at using reversal solutions were also good at using both familiar and novel solutions (Shelton, Marchette, and Brockman, in prep). This may be an

indication that reversals represent a hybrid of both novel and familiar solutions, in that a person is taking a familiar solution and manipulating it to create a novel one. But beyond this, little is known about how the capacity to use reversals may impact how we navigate.

1.3.4 Summary. As illustrated by the evidence reviewed above, previous research has focused on examining subjective preference for different kinds of information or solutions rather than examining how the capability to use each kind of solution relates to successful navigation. Therefore, in order to better understand how the ability to perform these solutions may relate to one's overall ability to successfully navigate, it is ideal to measure participants' observed ability to use these solutions. Doing this, in conjunction with measures of preference and bias in solution use, will allow us to understand how the relative contributions of capacity for specific solutions and propensity to use those solutions.

Finding that only the capacity for novel solutions is predictive of successful navigation would be consistent with previous research which has equated successful navigation with good environmental learning. Finding that multiple kinds of capacities predict success would indicate that not only has that view been incomplete, but that there are multiple ways one can be successful when navigating. On the opposite end of the spectrum, finding that none of these capacities relate to success could be an indication that it is not how good one is with a particular solution that allows them to get to their goal location, but some other factor, for example the solutions they tend to use.

1.4 Spatial Skills

The final set of factors we will review is spatial skills. Spatial skills are a class of abilities that allow us to imagine and reason about the objects and the relationships among objects in the world. A great deal of work has been done to try to isolate specific kinds of spatial

skills, and some of these abilities have been associated with aspects of navigation. We focus on three such skills—mental rotation, spatial perspective taking, and spatial working memory.

These skills have been shown to relate to some aspect of environmental learning, as described in more detail below, but none have been directly related to success when navigating in a situation in which multiple solutions are possible.

1.4.1 Mental rotation. Mental rotation is the ability to imagine the changing view of an object as it rotates in space about one or more axes (e.g., imagining how to properly rotate a suitcase to fit into an already full trunk). Mental rotation has been extensively tested using measures that require matching rotated figures, with the most common being the Mental Rotation Test (MRT; Vandenburg & Kuse, 1978). Scores on the Mental Rotation Test have been broadly associated with processing the global structure of an environment. For example, people with higher Mental Rotation Test scores tend to report preferences for using the structure of an environment rather than using previously traveled paths when navigating (Pazzaglia & DeBeni, 2001).

Behaviorally, mental rotation ability has been associated with the ability to correctly trace previously navigated paths onto a 2-dimensional map (Kozhevnikov et al., 2006). It was also related to success at remembering and navigating to hidden locations in a single-room navigation task (Astur et al., 2004). Another study found a relationship between mental rotation ability and accuracy at making distance and direction estimates and drawing a map of an environment (Hegarty et al., 2006). All of these tasks require knowledge of the structure of the environment. Consistent with this relationship to global structure learning, Shelton and Gabrieli (2004) found that brain activation in regions associated with spatial learning was correlated with Mental Rotation Test scores for trials that required utilizing global structure. Interestingly, in a separate

study Marchette et al. (2011) found no correlation between mental rotation ability and an individual's tendency to *spontaneously* use global structure strategies. Taken together, these results indicate that mental rotation ability is related to how well one uses the structure of the environment when navigating and their preference for using these strategies, but not how often they actually choose to use such strategies.

1.4.2 Spatial perspective taking. Spatial perspective taking is the ability to imagine the world from different points of view. For example, imagine having left a paper with an important phone number in the desk in your office. When you call a colleague to have her look for it, you will need to imagine what the office looks like from her perspective in order to guide her to the correct drawer.

Perspective taking has been distinguished from mental rotation by the profiles of response times produced by the tasks (see Zack & Michelon, 2005 for review). Briefly, for participants performing a mental rotation task, response time increase linearly with the number of degrees the object is rotated. In a perspective taking task, the response profile is flat; there is no increase in response time with an increase in size of rotation. These abilities also load on different factors in a factor analytic study (Hegarty & Waller, 2004). This distinction is further supported by neurobiological evidence that these two processes engage different neural systems (Kosslyn et al., 1998; Zacks et al., 1999).

In a factor analytic study, perspective taking ability was found to mediate the relationship between general spatial ability, a composite of other spatial abilities, and environmental learning measures, such as estimates of Euclidean distance and direction (Allen et al., 1996). This provides an indication that perspective taking may be important for one's success when navigating. However, other studies have found that perspective taking ability relates to strategy

use, but not overall success. Better perspective taking ability has been shown to be related to one's propensity to use global structure strategies as opposed to habitual strategies when navigating in virtual environments (Furman et al., 2014; Marchette et al., 2011). This was the case for both behavioral measures of navigation and for measures of activation of the relevant neural systems when learning the environment (Marchette et al., 2011) and when subsequently navigating through it (Furman et al., 2014). In these studies, neither perspective taking ability nor solution use was related to overall success. Taken together, these studies indicate that perspective taking ability may have an indirect effect on navigational success by mediating the effect of other abilities and may influence the kinds of solutions people use, but does not directly relate to successful navigation.

1.4.3 Spatial working memory. The next spatial ability, spatial working memory, is the ability to maintain and manipulate spatial information in memory (Shah & Miyake, 1996). For example, a person might turn off the lights in a hotel room at night and need to walk through it in the dark in order to go to bed. To do this without running into furniture, he/she would need to hold the locations of the furniture in the room in their working memory so that they could determine the open walkways. Higher spatial working memory capacity has been correlated with higher accuracy at estimating distances (Allen, Kirasic, Dobson, Long, & Beck, 1992; Hegarty, Montello, Richardson, Ishikawa, & Lovelace, 2006), estimating directions (Hegarty et al., 2006), and drawing maps (Allen et al., 1992), suggesting that greater capacity for spatial information is related to greater proficiency at learning the spatial relations between locations in an environment. In these studies, spatial working memory was measured as an individual's ability to select complex spatial arrays from a field of distractors after a short delay (Allen et al.,

1996) and an individual's ability to remember sequences of directions (arrows pointing in 45° intervals, 0°, 45°, 90°, etc.) after a short delay (Hegarty et al., 2006).

Consistent with these correlations, when spatial working memory was taxed by requiring participants to do a secondary task, individuals committed more errors when navigating (Coluccia, Bosco, & Brandimonte, 2007; Garden, Cornoldi, & Logie, 2002). In these studies, spatial working memory was loaded by instructing participants to tap a random pattern on a 3 x 3 keypad. This finding suggests that some aspects of spatial working memory are engaged during navigation. Together with the results above, these results suggest that spatial working memory is important for environmental learning and may be important for successful navigation.

1.4.4 Summary. In summary, although perspective taking abilities appear to only be related to *how* one navigates, mental rotation and spatial working memory appear to be associated with how well one learns the relationships among objects in an environment and the structure of the environment. These aspects of environmental learning could be critical to how successful a person tends to be when they navigate, particularly a person who uses solutions involving the global structure of the environment. But a direct connection between these spatial skills and successful navigation has not been made. Thus, although previous evidence suggests that spatial skills are relevant to navigation, whether these spatial skills can predict how *successfully* one tends to navigate remains an open question.

Finding unique contributions of spatial skills to navigational success would indicate that the act of navigating successfully is engaging spatial skills above and beyond the engagement of any specific capacity for using a solution. Depending on the relationships between other constructs, this may indicate that selecting an appropriate solution engages spatial skills. Alternatively, it is possible that spatial skills are related to navigational success, but are not unique predictors. This

would indicate that spatial skills are contributing to other processes, which are in turn directly predicting success. For example, the literature suggests that spatial skills are particularly important for learning the global structure of an environment. Thus it could be the case that spatial skills contribute to the capacity to use novel solutions, which relies on learning the global structure of an environment, and that capacity in turn uniquely predicts success. Finally, it could be the case that spatial skills have no relationship with successful navigation. Given previous research demonstrating a relationship between spatial skills and other aspects of navigation, it is unlikely that spatial skills simply aren't engaged when navigating. Thus this would likely indicate that either there are solutions one can use which do not require high spatial abilities to be successful, or that higher spatial abilities are not critical to success with any solutions.

1.5 Interim Summary

The above review has identified three categories of possible predictors of successful navigation: the selection of solutions, the capacity for those solutions, and spatial skills. Previous research on this topic has focused on the role of environmental learning rather than the simpler and more holistic goal of understanding what makes some people better able to get from one location to another. Based on these previous studies, we might expect that spatial skills, the preference/bias to use novel solutions, and the capacity to use novel solutions will predict successful navigation. But, to the extent to which the environmental learning is only telling a partial story about success, we would also expect to find that the capacity for other kinds of solutions will relate to success and that individuals who use a variety of solutions, allowing them to use solutions that better fit their abilities and their current situation.

1.6 Methodological Concerns

In order to properly examine how these constructs may predict how successfully one navigates, we first need a set of appropriate methods to measure these constructs. Many of these measures already exist in the literature. Appropriate and reliable measures already exist for mental rotation ability (Vandenberg & Kuse, 1978), spatial working memory, (Gmeindl et al., 2011), and preference for solution use (Pazzaglia & DeBeni, 2001). What remains are measures of bias and capacity for different solutions when navigating and a measure of how successfully one tends to be when navigating.

An ideal starting point for such behavioral measures is the Dual Solution Paradigm (DSP; Marchette et al., 2011), a virtual navigation task. In the initial encoding phase of this task, participants are shown several repetitions of a circuitous tour through a virtual environment which contains various objects. Then, in the subsequent navigation phase, participants are placed at locations along the tour path, rotated 360° to orient them in the space, and then instructed to find one of the objects on each trial. Critically, there are multiple possible paths to each target, which allows for the measurement of which solutions a participant uses. On each trial, participant could retrace a segment of the familiar path that was followed during the initial encoding phase (familiar path solution). Alternatively, a participant could use a novel shortcut path that they never directly experienced but could be deduced from the structure of the environment as revealed during initial encoding. Participants could also wander and take longer novel paths or not successfully reach their location, but such behaviors were extremely rare. For each participant, a solution index (SI) is derived from behavior by first categorizing each successfully completed trial according to which solution was selected. The SI is then calculated as the proportion of successfully completed and classifiable trials on which a participant took a

shortcut as opposed to a familiar path. As such, the SI is a measure of an individual's propensity to engage a global structure solution relative to a familiar path solution.

Although the DSP is a powerful tool for measuring navigational behavior, the paradigm has some specific limitations. First, the DSP uses a lengthy initial encoding phase prior to the navigational performance needed for the behavioral assessment. This is quite time consuming and makes it impractical to use multiple versions of this paradigm in the same study, as would be necessary if those methods were used to measure bias, capacity, and success. Another concern stems from the large number of trials that would be required to measure bias, capacity, and success. The DSP uses a single environment and thus learning can continue to occur as the test trials progress. This isn't particularly concerning in normal circumstances, but given the vast number of trials needed here, this could lead to participants overlearning the environment and potentially bias the measures. Finally, success rates were extremely high in this paradigm. This is ideal for measuring bias because a trial needs to be successful in order to classify the solution used with certainty and thus higher success rates allow for more trials that can be used to compute bias. But, obviously, this is not ideal for producing a range of success rates that would be necessary to understand factors relating to success.

Together, these limitations suggest the need for a new measure that complements the DSP in order to properly investigate the predictors of successful navigation. The critical feature of this measure will be that it uses the basic methodology of the DSP, but learning and testing will be encapsulated into a single trial. This allows the measure to be scaled to an appropriate size for the experimental purpose. It also allows for multiple environments, which reduces that possibility of someone overlearning the environment. The initial goals of the following experiments were to 1) establish the validity of such a measure and 2) determine the number of

trials required to obtain a stable measure. In these experiments, the focus was to establish a valid behavioral measure of bias. Once that has been established, the specifics of the environment can be tweaked to create a wider range of success rates.

Chapter 2: Development of a Single-Trial Navigation Paradigm

2.1 Experiment 1 Introduction

The goal of this experiment is to establish a new performance-based measure of navigation stemming from the dual-system framework used by Marchette et al. (2011) to develop the DSP which we will call the Spatial Learning Styles Assessment (SLSA). The critical feature of this measure will be that, in contrast to the protracted learning and navigation phases in the DSP, in the SLSA each trial will consist of a brief learning phase followed by a navigation phase. This allows the SLSA to be scaled to an appropriate size for a given experimental purpose and allows for multiple environments, which reduces that possibility of participants overlearning the environment. These critical features will make it ideal for the series of measures needed for a thorough investigation of the factors influencing successful navigation, as described above.

This experiment was designed to compare and contrast the measures obtained from the SLSA and DSP to determine the degree to which they are measuring the same constructs. We anticipated that the two paradigms will be related in both success rates and the solution indices. Finding this would be consistent with the SLSA being a valid measure of spatial learning styles.

We also compared the two performance-based measures to capacities and preferences identified via self-report. The Questionnaire on Spatial Representation, which measures preference for different kinds of information when navigating (Pazzaglia & DeBeni, 2001), was used as a proxy for self-reported preference for different kinds of solutions. This was done because these different kinds of information underlie the different kinds of solutions captured by the performance-based measures. Correlations between the performance-based measures and

self-report results offer insights into how much behavior is driven by processes available to explicit access or reflection.

We also examined correlations among these measures and spatial skills to provide additional insights into what different learning styles and preferences might mean for a broader characterization of an individual's spatial learning. Two such spatial skills were examined – mental rotation and perspective taking (described in detail in Chapter 1). Due to time constraints, spatial working memory measures were not included in these experiments. Based on previous research, we anticipated that these spatial skills might be related to individual's tendency to use global structure solutions (Allen et al., 1996; Hegarty et al., 2006) and potentially their overall success rates (Astur et al., 2004).

2.2 Methods

2.2.1 Participants

Eighty-seven Johns Hopkins University students participated in exchange for extra credit in psychology courses. The data from one male participant was excluded for noncompliance (no movement during the majority of navigation trials). This left us with a total of 86 participants (47 female, mean age: 20.1 years, age range: 18-51 years).

2.2.2 Materials and Procedure

All participants completed the DSP and the SLSA as well as a set of pencil and paper inventories that included self-report and spatial skills assessments. The order of the experimental tasks and the set of inventories were counterbalanced across participants.

2.2.2.1 Dual Solution Paradigm (DSP; Marchette et al., 2011). During the initial encoding phase, participants viewed a 62-second video tour through one of two 11x11 virtual mazes (constructed in Portal; www.valvesoftware.com). The tour always followed the same path

through the environment and was repeated 9 times. Following the initial encoding phase, participants practiced navigating using the arrow keys on the keyboard in a different environment. Once participants were familiar with the controls (typically 1-2 minutes), they completed 16 unique retrieval trials in random order. Each trial began in a small blue lobby which displayed a message indicating the target object to be located on that trial.

Participants were then placed at a location in the environment along the initial encoding path. To avoid any bias in strategy, participants were placed at this location facing an outside wall and experienced a 6 second, 360° passive rotation to ensure they could establish their position and orientation in the space. Participants were then given 45 seconds to navigate to the target object. On each trial, the participant could use either a segment of the familiar encoding path between the trial start and the target location or a novel shortcut path, which was by definition a path that led from the trial start to the target with a shorter distance than the familiar path and had been visible but not directly experienced during initial encoding (see Figure 1 for a diagram). A trial ended when the participant reached the target or ran out of time. At the end of the trial, participants were placed back in the virtual lobby to start the next trial.

For each trial, the specific path navigated and whether or not the target was reached before the time limit were recorded. Success rates and solution indices (SI) were calculated from these values. Success rates were calculated as the percentage of trials in which a participant reached the goal in the time limit. A solution index (SI) is calculated by taking all trials for which the solution could be classified as either familiar path use or shortcut use and calculating the proportion of those trials for which the participant used the available shortcut, as below:

$$\frac{\# \text{ shortcuts}}{(\# \text{ shortcuts} + \# \text{ familiar paths})}$$

This provides a metric for the relative reliance on repeating what is familiar, perhaps more habitually, by taking the familiar path ($SI < 0.5$) or on deriving global structure and taking advantage of novel shortcuts ($SI > 0.5$).

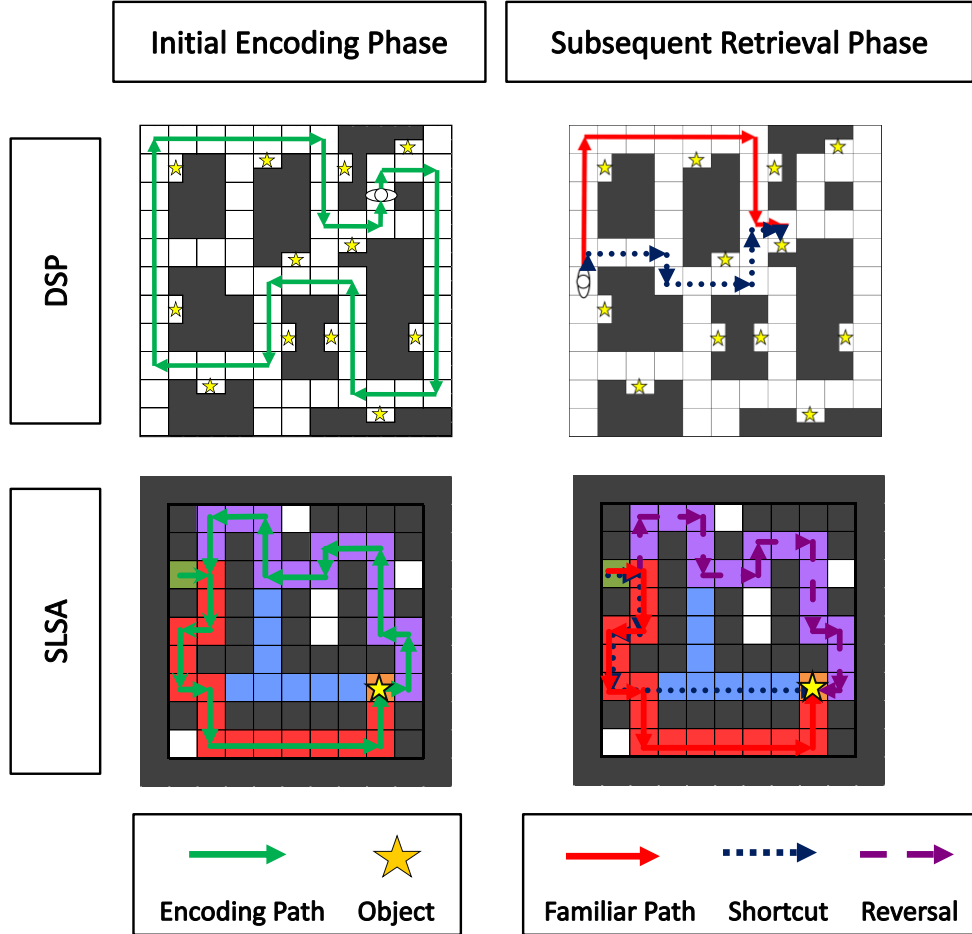


Figure 1. Example diagrams of the Dual Solution Paradigm (top) and Spatial Learning Styles Assessment (bottom). The images are on the same scale to show the relative sizes in the two paradigms.

2.2.2.2 Spatial Learning Styles Assessment (SLSA). For this task, 16 different 9x9 virtual mazes were constructed in Portal; (www.valvesoftware.com). Each environment contained a different arrangement of hallways and each had a unique set of wall and floor textures. On each trial, participants were placed in one of the 16 environments at a designated

start location and were led along the start-to-goal path to a goal object (a wooden door). Participants viewed the goal object for 2 seconds and were then led back to the start location along a different path, the goal-to-start path (see Figures 1 & 2). When they reached the start location, participants were rotated to face the same direction they had faced at the beginning of



Figure 2. Screenshot of SLSA trial from the participant's view.

the trial and instructed to navigate to the goal object.

Participants were given 35 seconds to reach the goal object before the trial was considered unsuccessful. Each environment contained 3 paths that lead to the goal object: the start-to-goal path, the goal-to-start path, and a novel shortcut that was shorter than the other two paths, visible during the initial learning phase, but never directly experienced by the participant. Half of trials used the same physical structure as another trial except that the start-to-goal and goal-to-start paths were reversed. Each environment used a different set of wall and floor textures. Participants initially completed one practice trial to familiarize them with using the arrow keys on the keyboard to navigate. Trial order was determined by creating 4 random sets of all trials and assigning those 4 sets across participants, such that use of each order was roughly equally distributed across participants (21-22 participants per order). For each trial, the path

navigated and whether the participant reached the goal before the time limit was recorded.

Success rate and SI were calculated using the same approach as in the Dual Solution Paradigm.

Given that we were interested in comparing Dual Solution Paradigm and SLSA, we excluded trials on which participants used the reversed path (goal-to-start) because this path did not occur in the Dual Solution Paradigm. On average, participants used reversals on about 3.5 (of 16) trials on average (range 0-10). Moreover, the use of reversals was not correlated with any other variables of interest. Nevertheless, this selection may provide additional information about learning style that can be further assessed with more power in a future study, highlighting a possible methodological advantage of the SLSA in comparison to the DSP.

2.2.2.3 Spatial inventories. All participants also completed a battery of standard measures of spatial skills and preferences. These inventories were intermixed with other measures that are not relevant to the current paper (primarily exploratory items) and the order of these inventories was randomized across participants.

2.2.2.3.1 Santa Barbara Sense of Direction Scale (Hegarty et al., 2002). This task indexes self-reported sense of direction, or one's general navigational prowess. Participants rate their agreement with 15 Likert-scale items such as "I am good at giving directions" and "I have a poor memory for where I left things" on a 1 to 7 scale. Scores are calculated out of 105, with higher scores reflecting better subjective sense of direction.

2.2.2.3.2 Questionnaire on Spatial Representations (Pazzaglia & DeBeni, 2001). This task indexes self-reported preference for the use of different navigational strategies by asking participants to rate the extent to which 6 Likert-scale items describe their experiences and preferences during navigation and spatial learning. The items can be broken down into 3 subscales, one of which assesses the preference for the use of landmarks, familiar routes, and

global structure, with possible values ranging from 2-10 points for each strategy. The latter two subscales were used to create an index of relative preference for familiar paths vs. global structure by taking a difference score, ranging from -8 (strong familiar path preference) to +8 (strong global structure preference), which we refer to as the QSR-Style.

2.2.2.3.3 Mental Rotation Test (Vandenberg & Kuse, 1978). This task measures the ability to imagine and compare objects that are rotated relative to one another. On each item, participants decide which 2 of 4 objects are rotated versions of a reference object. The test is separated into two parts with 10-items each, and participants are given 3 minutes to complete each section. Scores are calculated out of 40 (up to 2 points per item).

2.2.2.3.3 Spatial Perspective Test (Kozhevnikov & Hegarty, 2001). This task measures the ability to imagine arrays of objects from different visuo-spatial viewpoints. For each item, participants view a 2-dimensional image of an array of objects and are asked to take an imagined perspective (e.g., “Imagine you are at the flower facing the stop sign.”) and determine how to point to a third item in the array (e.g., “Point to the cat.”) Responses are given by drawing a line on a circle where “up” represents the imagined heading (flower to stop sign) and the drawn line indicates the direction of the target. Participants are given 5 minutes to complete 12 questions. Scores are calculated by subtracting the average angular error from 180°.

2.3 Results

Throughout the subsequent sections, the results rely heavily on correlations. Given the number of correlations possible in the entire study, we had to make careful decisions about how to correct for multiple comparisons. In all tables, we offer information about different possible criteria, from the most liberal to the most conservative so that the reader has the option of considering these results at different levels. However, we set out with the criterion of correcting

for the relevant subset of correlations within each data set and variable grouping. This is signified in the tables using a unique symbol (⊕). For this reason, we do not report p-values in the text for these correlations. Additional or alternative symbols indicate which correlations meet more or less conservative criteria.

The structure of the results is as follows. First, we asked how measures from the DSP compare to measures from the SLSA. Next, we ask how the performance-based measures relate to self-report and spatial skill measures. This is done to understand how these measures relate to the performance-based measures and to determine whether the two performance-based measures are displaying the same relationships with other tasks. Finally we present Monte Carlo simulations to understand the stability of measures from the SLSA and understand whether fewer trials can be used without damaging the reliability of the measure.

2.3.1 Full & Reduced Datasets

In order to answer questions about both success rate and navigational learning style, we established two datasets. First, we used the entire dataset (referred to as full) for analysis of success rate. This allows us to see the full range of performance. However, in order to accurately examine style, we had to have enough completed trials for any given participant to calculate the SI. Based on previous experience with the DSP, we excluded any participant who completed less than 50% of trials in order to calculate the SI. This excluded 14 participants (13 female), leaving 71 participants (35 female). We then applied the same criteria for the SLSA, but no additional participants were excluded. All analyses of success rate are presented on the full dataset ($n = 85$) and the reduced dataset ($n = 71$) except in cases that include SI as part of the analysis. SIs were only calculated for the participants in the reduced set.

Table 1. Means and standard deviations for all measures. Significant gender differences are displayed in bold.

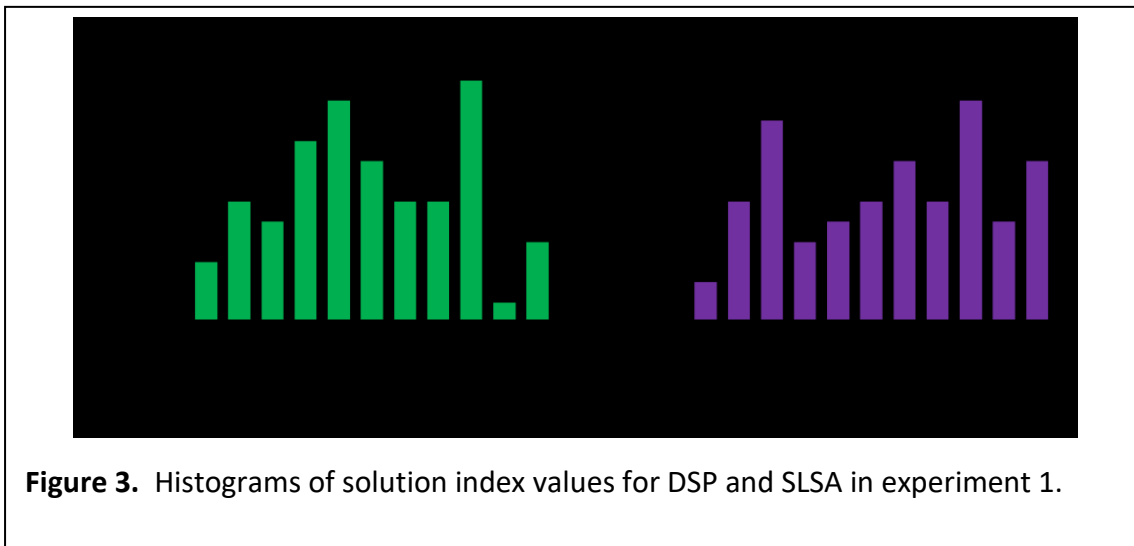
Measure	Overall	Male	Female	Comparison
Mental Rotation Test	19.55 (8.95)	22.7 (9.2)	16.6 (7.7)	$t = 3.27, p = 0.001$
Non-Sequential Corsi Block	7.45 (2.33)	7.27 (1.78)	7.54 (2.55)	$t = 0.62, p = 0.537$
QSR-Style	-0.34 (2.46)	0.23 (2.25)	-0.87 (2.54)	$t = 2.27, p = 0.026$
SLSA Familiar Rate	0.34 (0.24)	0.35 (0.24)	0.34 (0.24)	$t = 0.12, p = 0.909$
SLSA Novel Rate	0.40 (0.26)	0.40 (0.26)	0.40 (0.26)	$t = .008, p = 0.939$
SLSA Reversal Rate	0.26 (0.19)	0.26 (0.20)	0.26 (.019)	$t = .009, p = 0.931$
SLSA SI	0.53 (0.30)	0.52 (0.31)	0.54 (0.30)	$t = 0.27, p = 0.787$
SRA Success Rate	0.55 (0.25)	0.62 (0.22)	0.49 (0.25)	$t = 2.60, p = 0.011$
Required Familiar Path	0.61 (0.20)	0.69 (0.16)	0.54 (0.21)	$t = 4.04, p < 0.001$
Required Novel Path	0.53 (0.18)	0.60 (0.17)	0.48 (0.18)	$t = 3.34, p = 0.001$
Required Reversal Path	0.71 (0.18)	0.79 (0.16)	0.65 (0.17)	$t = 4.20, p < 0.001$
Flexibility of Solution Use	0.26 (0.16)	0.26 (0.17)	0.26 (0.15)	$t = 0.08, p = 0.935$

2.3.2 Summary Data

Before proceeding to the target questions of interest, we examined the descriptive statistics for all measures in both datasets (with the exception of SI, which can only be evaluated

in the reduced set), including a comparison of males and females to assess possible gender differences. Table 1 shows the summary data and comparisons.

We observed the typical male advantage in mental rotation on both the full, $t(84) = 5.38$, $p < 0.001$, and reduced data, $t(69) = 4.16$, $p < 0.001$, as well as on the Santa Barbara Sense of Direction Scale, $t(84) = 3.61$, $p = 0.001$ and $t(69) = 3.67$, $p = 0.001$, for full and reduced, respectively. Unexpected gender differences were observed on the measures of success and style from the DSP and SLSA. Males had higher success rates than females on the DSP in the full set, $t(84) = 3.32$, $p = 0.001$, but not the reduced set, $t(69) = 1.57$, $p = 0.122$, a finding consistent with the exclusion of more females based on the exclusion criteria. For the SLSA, males had higher success rates than females in both the full, $t(84) = 2.87$, $p = 0.005$ and reduced sets $t(69) = 3.80$, $p < 0.001$.



Using only the reduced dataset, SI was calculated for the DSP and the SLSA separately using equation 1 above. A full range of SI was observed in both the DSP and SLSA (Figure 3). A gender difference was observed in SI, such that males tended to have SI values, indicative of more shortcuts, and females had SI values indicative of more familiar paths, in both the DSP, $t(69) = 3.80$, $p < 0.001$ and in the SLSA, $t(69) = 4.35$, $p < 0.001$. This is the first time a gender

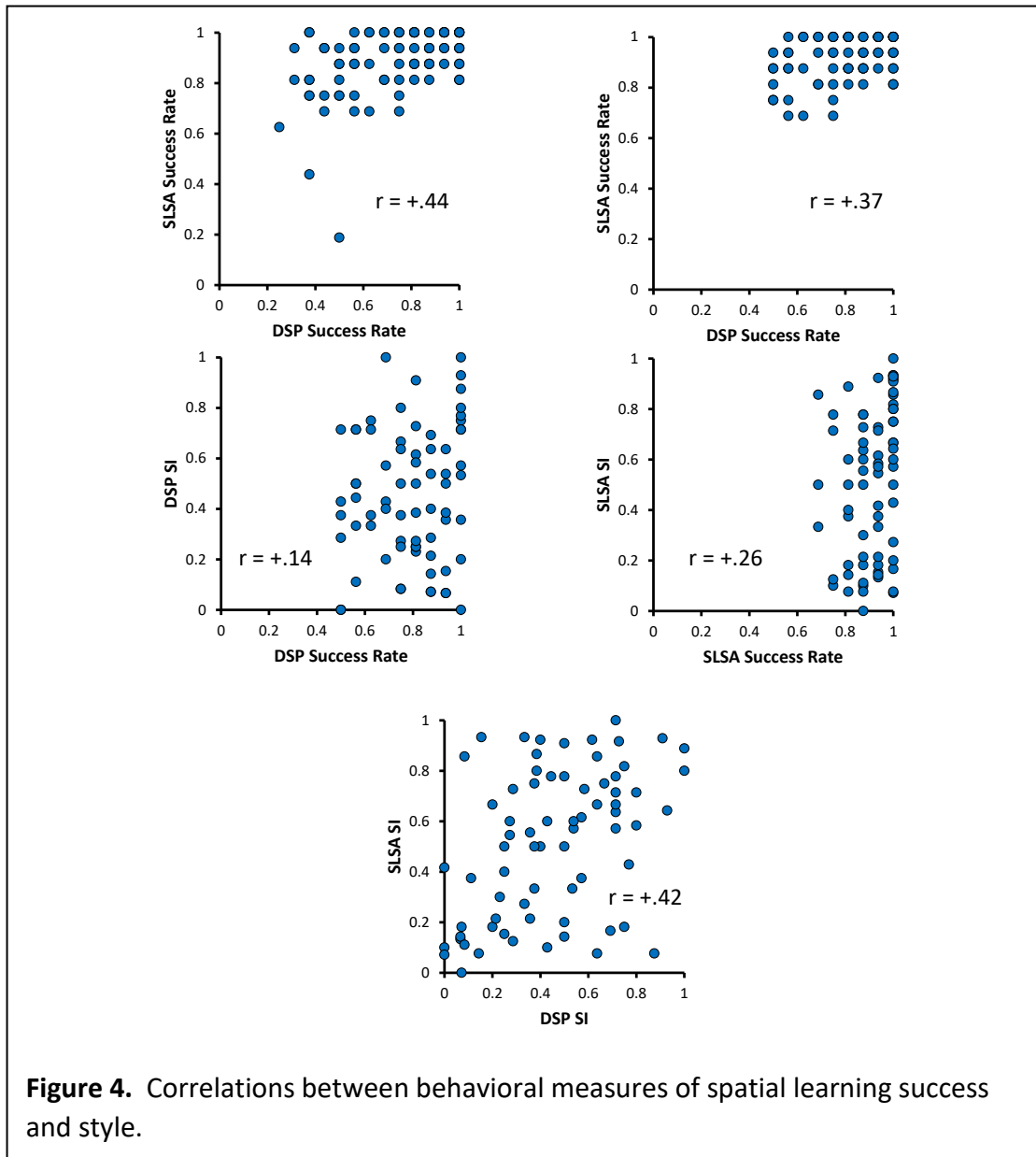
difference in solution use has been observed (see Furman et al., 2014; Marchette et al., 2011), which suggests that it may be sample-specific. To account for this issue, subsequent correlational analyses are done both overall and for males and females separately.

2.3.3 Comparison of Dual Solution Paradigm & Spatial Learning Styles Assessment

The first critical test of the SLSA was to see whether measures of success and style in the SLSA with the analogous measures in the DSP. There were significant positive correlations between DSP and SLSA success rates in the full, $r = +.44$ and reduced, $r = +.37$, data. Similarly, there was a significant positive correlation between Dual Solution Paradigm and SLSA SIs, $r = +.42$. This suggests that the two tasks captured similar individual differences. Success and SI were not correlated within the Dual Solution Paradigm, $r = +.14$, but were correlated within the SLSA, $r = +.26$, such that individuals who used proportionally more shortcuts than familiar paths were more successful than participants who used more familiar paths than shortcuts (see Figure 4). There was a gender difference in the relationship SLSA SI and success rate, such that this relationship was weak and negative for females, $r = -.14$, and stronger and positive for males, $r = +.39$. A Fisher's Z test revealed that this difference was significant $z = 2.19$, $p = 0.029$. Thus it appears that for males, the use of novel shortcuts was related to overall success in the SLSA. There were no other significant gender differences, $ps > 0.07$.

2.3.4 Relationships among Performance-Based Measures, Self-Reports & Spatial Skills

Next we were interested in whether our performance-based measures were related to self-report measures and spatial skill measures. Correlations among these measures were examined in the full and reduced data sets overall, and for males and females separately. As shown in Table 2, a number of typical correlations were replicated. However, a substantial correlation between the Mental Rotation Test and the Spatial Perspective Test, particularly among male



participants, was observed. The Mental Rotation Test has largely been associated with aspects of

good navigation, whereas the Spatial Perspective Test has been associated with flexibility and

Table 2. Correlations (r) among the individual differences test broken down by dataset and gender in Experiment 1

Overall (Reduced Dataset)			
	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Santa Barbara Sense of Direction	+ .08	+ .26 †	+ .13
QSR-Style	-	+ .01	+ .09
Mental Rotation Test	-	-	+ .32 ☆
Female (Reduced Dataset)			
	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Santa Barbara Sense of Direction	+ .24	+ .10	+ .19
QSR-Style	-	+ .01	+ .07
Mental Rotation Test	-	-	+ .08
Male (Reduced Dataset)			
	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Santa Barbara Sense of Direction	- .14	+ .12	+ .05
QSR-Style	-	- .09	+ .10
Mental Rotation Test	-	-	+ .53 ☆**
† p < 0.05 uncorrected ☆ p < 0.05 corrected for relevant subset of 6 correlations. ☆* p < 0.05 corrected for all 18 correlations in a given dataset (Full or Reduced). ☆** p < 0.05 corrected for all 36 correlations presented here.			

style, but these differential relationships depend on Mental Rotation Test and Spatial Perspective Test measuring separable skills. In the previous samples, Mental Rotation Test and Spatial Perspective Taking test scores have not been highly correlated (Marchette et al., 2011; Furman et al., 2014). The observation of a correlation in the present data raises questions about whether, in this sample, tasks are measuring distinct constructs and thus whether we will see correlations consistent with previous results from samples in which these tasks were measuring distinct constructs.

To preview the results, we did not replicate most of the previously observed relationships with the Spatial Perspective Test. In fact the relationships we found were consistently the same pattern as found for the Mental Rotation Test, but not as strong. We attribute this to Spatial Perspective Test in this sample being biased to reflect mental rotation more than perspective-taking ability. Anecdotally, research assistants running this study reported many participants attempting to turn or draw on the page while completing this measure (they were immediately instructed not to and allowed to continue), which would be consistent with participants approaching this as a mental rotation task rather than engaging in perspective taking. Based on all of these observations, we were not confident that we had captured appropriate constructs with the Spatial Perspective Taking test and did not include it in the reported analyses.

The following sections investigate how self-report measures and spatial skill measures relate to aspects of the performance-based measures. In particular, we are interested in the extent to which the relationships among self-report, spatial skill, and performance-based measures are similar when using the DSP and SLA. This will be done in two sections. The first will look at how these measures relate to measures of successful navigation. The second will look at how these measures relate to measures of navigational style.

2.3.4.1 Successful navigation.

2.3.4.1.1 Self-report measures.

2.3.4.1.1.1 Santa Barbara Sense of Direction Scale. As shown in Table 3, success rates were generally correlated with Santa Barbara Sense of Direction score. This correlation was positive and significant for the DSP for the full dataset, $r = +.34$, but not significant for the reduced dataset, $r = +.25$, suggesting that the poor performers who were excluded from the reduced set were, in part, driving the correlation between DSP success rate and Santa Barbara Sense of Direction Scale scores. For the SLSA, this correlation was positive but not significant for either dataset, $r = +.21$ and $r = +.26$ for full and reduced dataset, respectively. Interestingly, the numerical pattern is opposite, with the reduced set showing a larger correlation (i.e. a larger effect size), but these correlations were not statistically different. In all cases, the correlations for females were numerically larger than for males, but Fisher's z tests revealed that these were not significant, $ps > .75$ and $> .15$ for full and reduced datasets, respectively.

2.3.4.1.1.2 QSR-Style. QSR-Style, a measure of relative preference for different kinds of solutions, had a similar non-significant positive correlation with success rate in the DSP, $r = +.26$ and $r = +.24$ on full and reduced dataset, respectively. These correlations were numerically larger for females than for males, although these differences not significant by a Fisher's z , $ps > 0.07$. There was a non-significant positive correlation with success rate on the SLSA in the full dataset, $r = +.25$, but a significant correlation in the reduced dataset, $r = +.38$. This suggests that the excluded data (those individuals at the lowest end of the success continuum) were driving down the positive relationship rather than exacerbating it. Again, correlations were larger for females than for males, but the differences were not significant, $ps > 0.60$.

Table 3. Correlations (r) between each dependent measure from the navigation tests and each of the individual differences measures in the full dataset broken down by gender in Experiment 1.

Overall (Full Dataset)					
		Santa Barbara Sense of Direction	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Dual Solution Paradigm	% Complete	+0.34 ★**	+0.26 †	+0.52 ★**	+0.37 ★**
SLSA	% Complete	+0.21 †	+0.25 †	+0.45 ★**	+0.23
Female (Full Dataset)					
		Santa Barbara Sense of Direction	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Dual Solution Paradigm	% Complete	+0.27	+0.37 ★	+0.52 ★**	+0.43 ★*
SLSA	% Complete	+0.15	+0.16	+0.42 ★	+0.43 ★
Male (Full Dataset)					
		Santa Barbara Sense of Direction	QSR-style	Mental Rotation Test	Spatial Perspective Taking
Dual Solution Paradigm	% Complete	+0.24	+0.004	+0.27	+0.24
SLSA	% Complete	+0.08	+0.27	+0.30	-0.02
† p < 0.05 uncorrected ★ p < 0.05 corrected for relevant subset of 4 correlations for each dependent measure within ★* p < 0.05 corrected for all 24 the a given dataset. ★** p < 0.05 corrected for all 36 correlations presented here.					

In summary with respect to success rates, the results show that, in general, self-report measures do not correspond well with their behavior, performance-based counterparts.

Furthermore, the DSP and SLSA measures of success rate are showing similar relationships to these self-report measures, indicating that the SLSA is measuring the same differences as the DSP. One exception to this was that in the full dataset, DSP success rate was correlated with self-reported sense of direction, whereas there was no such relationship in the SLSA. This is likely caused by the differences in variability in the success rates of the DSP and SLSA, mean success rate 72% and 89%, respectively, in the full dataset, supported by the lack of significant correlation in the reduced dataset, which has a reduced range of success rates. Importantly, this is an indication that in their current forms, the SLSA and DSP can offer suggestive evidence about predicting successful navigation, but the abbreviated range of success rates limits the conclusions that can be drawn.

2.3.4.1.2 Mental Rotation Test. Scores on the Mental Rotation Test had a significant positive correlation with DSP success rate for the full, $r = +.52$, but not the reduced dataset, $r = +.16$. These correlations were numerically larger for males than females, but not significant by a Fisher's z , $ps > 0.18$. Mental Rotation Test scores were significantly correlated with SLSA success rate in both the full, $r = +.45$, and reduced dataset, $r = +.41$. These correlations were numerically larger for males than females, but not significant by a Fisher's z , $ps > 0.22$. This finding is consistent with previous studies showing that better mental rotation ability is associated with more successful navigation (Astur et al., 2004; Kozhevnikov et al., 2006; Shelton and Gabrieli, 2004).

Given that previous research has indicated that mental rotation abilities may be particularly important for global structure solutions and that different possible successful solutions were possible in this study, we next explored the relationships between performance-based measures of success and spatial skills as a function of the different solutions. To that end,

we divided participants from the reduced dataset into groups based on their preferred strategies in the SLSA: familiar path users (used the familiar path on > 70% of trials, $n = 22$), global structure users (used shortcuts on > 70% of trials, $n = 24$), and mixed strategy users (everyone in between the other two groups, $n = 25$). Mental Rotation Test scores and success rates were correlated for global structure users, $r = +.62$, $p = 0.001$, and mixed strategy users, $r = 0.50$, $p = 0.011$, but not for familiar path users, $r = -.08$, $p = 0.723$. There was no difference in Mental Rotation Test scores between familiar path users and global structure users ($t(44) = -0.833$, $p = 0.409$) or mixed strategy users ($t(45) = -0.854$, $p = 0.398$). These data may indicate that mental rotation is important for success when one has a preference for using the global structure.

In summary with respect to spatial skills, the results show that measures of success from the DSP and SLSA have different relationships with mental rotation ability. Mental rotation ability is correlated with success on the SLSA, in particular when an individual is using more global structure solutions, but not on the DSP. Given that the SLSA assesses navigation after far less exposure to the environment than the DSP, this may indicate that mental rotation abilities are critical for learning the global structure of an environment and may become less important when later attempting to use that information to navigate.

2.3.4.2 Navigational style (Solution Index).

2.3.4.2.1 Self-report measures.

2.3.4.2.1.1 Santa Barbara Sense of Direction Scale. As shown in Table 4, Santa Barbara Sense of Direction scores were positively but not significantly correlated with SI on the DSP, $r = +.19$, and the SLSA, $r = +.18$. There was no difference between females and males as confirmed by a Fisher's z , $ps > 0.49$.

Table 4. Correlations (r) between each dependent measure from the navigation tests and each of the individual differences measures in the reduced dataset broken down by gender in Experiment 1.

Overall (Reduced Dataset)					
		Santa Barbara Sense of Direction	QSR- Style	Mental Rotation Test	Spatial Perspective Taking
Dual Solution Paradigm	% Complete	+.25 †	+.24 †	+.16	+.15
	SI	+.19	+.03	+.24 †	-.14
SLSA	% Complete	+.26 †	+.38 ★**	+.41 ★**	+.25 †
	SI	+.18	-.02	+.18	-.23 †
Female (Reduced Dataset)					
		Santa Barbara Sense of Direction	QSR- Style	Mental Rotation Test	Spatial Perspective Taking
Dual Solution Paradigm	% Complete	+.36 †	+.43 ★	+.12	+.20
	SI	-.04	+.04	-.06	-.33
SLSA	% Complete	+.24	+.43 ★	+.27	+.21
	SI	-.08	-.21	-.08	-.58 ★**
Male (Reduced Dataset)					
		Santa Barbara Sense of Direction	QSR- Style	Mental Rotation Test	Spatial Perspective Taking
Dual Solution Paradigm	% Complete	+.02	+.01	+.05	+.08
	SI	+.12	-.07	+.18	-.05
SLSA	% Complete	-.05	+.32	+.29	+.30
	SI	+.09	+.06	+.004	-.08

† p < 0.05 uncorrected

★* p < 0.05 corrected for relevant subset of 4 correlations for each dependent measure within

★* p < 0.05 corrected for all correlations in the given dataset.

★** p < 0.05 corrected for all 36 correlations presented here.

2.3.4.2.1.2 QSR-Style. QSR-Style scores were not significantly correlated with SI for the DSP, $r = +.03$, or the SLSA, $r = -.02$. A Fisher's z revealed no significant gender difference for either correlation, $ps > 0.66$. In conjunction with the above lack of relationship between the performance-based measures and the Santa Barbara Sense of Direction, this indicates that implicit preferences are not being captured by these measures. In previous experiments, these self-report measures were associated with both the SI on the DSP and brain activation that distinguishes these styles (Furman et al., 2014), suggesting that these measures may not be reliable across different samples at picking up on the strategies people actually use when navigating in virtual environments.

In sum, we do not find support for self-report measures relating to performance-based measures of how individuals navigate. However, we did find that measures from the DSP and SLSA exhibit the same lack of relationship with these self-report measures. This is consistent with the two performance-based measures capturing similar individual differences. This emphasizes a potentially important difference between what people do and what they report that they do.

2.3.4.2.2 Mental Rotation Test. In this study, Mental Rotation Test scores were non-significantly, positively correlated with SI on the DSP, $r = +.24$, and the SLSA, $r = +.18$. In the full and reduced datasets, these correlations were not different between females and males, $ps > 0.28$. Consistent with previous studies (Marchette et al., 2010), mental rotation ability does not appear to predict solution use even though it is related to overall success.

In sum, these sets of analyses demonstrate that mental rotation ability is not related to individuals' biases for selecting specific kinds of solutions when navigating. Critically, this is

true for both the DSP and SLSA, indicating that they are measuring the same individual differences.

2.3.5 The Stability of the SLSA SI (Monte Carlo Simulations)

Finally, one of the goals in developing the new paradigm was to provide a shortened version of the task that could be used more efficiently in a battery of tasks. To that end, we examined how well subsets of trials represented the overall results by breaking down the dataset and running simulations.

2.3.5.1 Stability of SI. First, we considered how many trials were necessary to observe stable distributions of SI values. Every possible combination of n trials (n s ranging from 5-10) was taken from the full set of trials used in the experiment. For each subset, we calculated the SI for each participant and correlated those values with the participants' SI from the full set of trials. The distributions of correlations for each subset size are shown in Figure 5. We set our criteria as the smallest sample size that would yield a mean correlation coefficient of 0.85 or above with a standard deviation less than 0.05. Of these distributions, $n = 6$ met these criteria, suggesting this sample size might be the optimal compromise between task length and precision.

2.3.5.2 Stability of Observed Correlation. As an additional verification of the utility of a possible 6-trial version, we evaluated the stability of the observed correlations between the SLSA measures and the other measures of the study. For this purpose, correlations were calculated for all 8008 possible subsets of 6 trials. First, we looked at the extent to which measures from the SLSA were related to measures from the Dual Solution Paradigm. Across all 6-trial subsets, SLSA success rate was correlated with Dual Solution Paradigm success rate (mean $r = +.31$, $s = 0.09$). Similarly, across all subsets, SLSA SI was correlated with Dual Solution Paradigm SI (mean $r = +.32$, $SD = 0.05$). These findings are consistent with the Dual

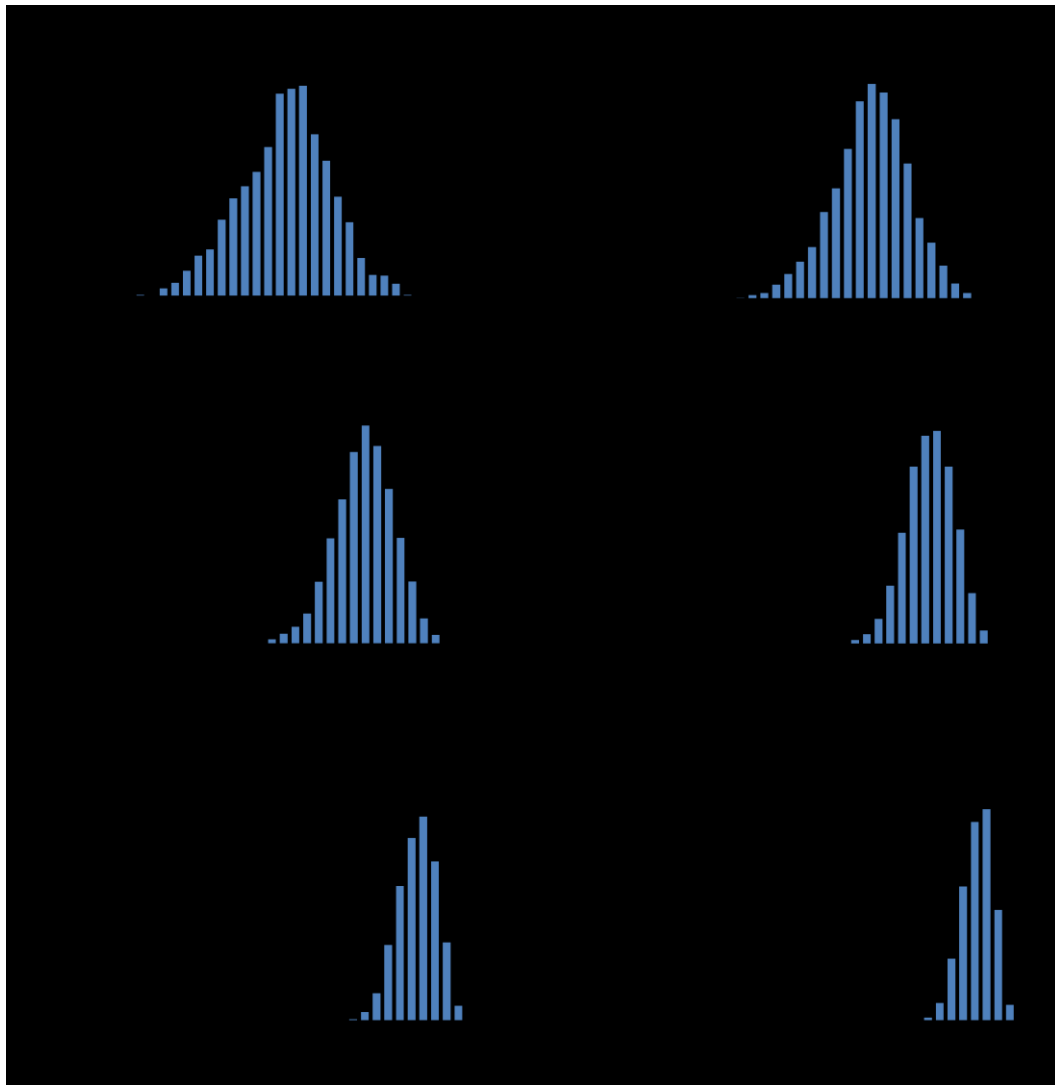
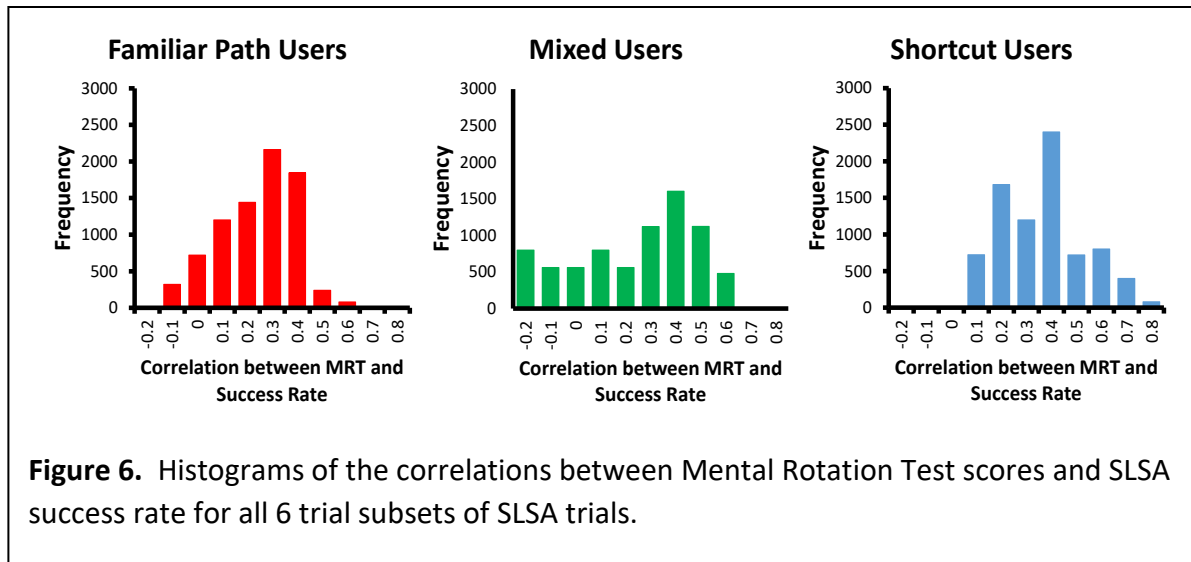


Figure 5. Histograms of correlations between SI as measured by a 16 trial SLSA and SI as measured by 5-10 trial versions of the SLSA. Every combination of 5-10 trials was used.

Solution Paradigm and SLSA picking up on much of the same variance in success rate and style, and support the use of subsets of SLSA trials in a shortened version.

Next, we were interested in the extent to which measures from the SLSA were related to self-report measures. Across all subsets of trials, Santa Barbara Sense of Direction scores were at best weakly correlated with SLSA success rates (mean $r = +.18$, $SD = 0.05$). This is consistent with the above finding that self-report measures of overall navigational ability only weakly relate



to performance-based measures. Similarly, across all subsets of trials, QSR-Style had virtually no correlation with SLSA SI (mean $r = -.01$, $SD = 0.06$). This is consistent with the above finding that self-reported preference for environmental information is not related to behaviorally measured biases in navigational behavior.

Finally, we explored how measures from the SLSA were related to spatial skills. Scores on the Mental Rotation Test were correlated with SLSA success rates (mean $r = +.27$, $SD = 0.8$). We then split participants into groups based on their preferred strategies using the same criteria as used in Experiment 1. Across all 8008 sets, the correlation between Mental Rotation Test scores and success for familiar path users had a range of $-.13$ to $+.55$ (mean $r = +.19$, $SD = 0.18$) and for shortcut users there was a range of $+.02$ to $+.74$ (mean $r = +.25$, $SD = 0.16$) (see Figure 6). This is consistent with mental rotation ability being related to successful navigation, particularly for global structure strategies, and an influence of environment on the relationship between mental rotation ability and success. These results indicate that the correlations among measures from the SLSA and self-report and spatial skills are stable in a short form version of the SLSA.

2.4 Discussion

The first concern in this experiment is whether the SLSA is capable of measuring how and how well one learns space and navigates in a similar fashion to the Dual Solution Paradigm. We found significant correlations between Dual Solution Paradigm and SLSA measures of success rate and SI. These relationships between the novel SLSA and the established Dual Solution Paradigm provide support for the SLSA as a valid measure of spatial learning style. The two performance-based measures also appear to be capturing navigational success in the same way, but it is important to note that in both success rates are at ceiling. The contention that these measures are capturing the same constructs is further supported by measures from the SLSA and DSP having, for the most part, the same relationships with self-reports and spatial skill measures.

The next critical question this experiment addressed was whether self-report measures correspond with these performance-based measures. There were non-significant correlations between self-reported navigational prowess and success on the performance-based measures and between self-reported preference for environmental information and performance-based measures of spatial learning style. Together, this indicates that, at least in some situations, participants do not have clear metacognitive access to how or how well they learn space.

An alternative explanation is that these self-report measures are not asking the right questions to probe factors that directly relate to performance. This is an open possibility for relating self-reported sense of direction. The Santa Barbara Sense of Direction Scale uses questions such as “I have a poor memory for where I left things”, “I enjoy reading maps”, “I have trouble understanding directions”, etc. which all relate to the construct of sense of direction, but may only be related tangentially related to successful navigation. Thus a productive future

line of research may be to investigate better self-report measures of successful navigation. An important first step to this line of work is to better understand what factors are contributing to successful navigation, which will be done in Experiment 3. It is also important to note that the relationship between self-reported and performance-based success may be limited by the high success rates in the performance-based measures, which will also be addressed in Experiment 3.

In terms of *how* individuals navigate, this possibility is less likely. The items of the Questionnaire on Spatial Representations directly ask about the kinds of information one uses (familiar routes versus a more map-like understanding of the structure of the environment). Although better self-report measures could be constructed to predict one's biases when navigating, for example by using the extent to which one uses habitual solutions to problems in other domains, these findings still suggest that individuals do not have clear metacognitive access to the methods they tend to use when navigating.

In summary, the results from Experiment 1 are consistent with measures from the SLSA capturing the same individual differences as measures from the DSP. Based on Monte Carlo simulations, we have some initial evidence that the SLSA can be reduced to 6 trials and remain a reliable measure. Experiment 2 will was designed to test this contention.

2.5 Experiment 2

The SLSA is a promising tool for future research on individual differences in spatial learning because it is capable of measuring spatial learning styles at an early point in learning and allows for trial-by-trial manipulations of environmental features and conditions that are not possible with previous measures. However, there are some practical considerations when using this tool. In most behavioral experiments time is at a premium because of participant fatigue, funding, and the availability of experimenters to run the experiments. Thus it is desirable to

reduce the length of measures as much as possible without losing reliability or predictive validity. The results from the above Monte Carlo simulations are consistent with a shortened version of the SLSA being a reliable measure of spatial learning style, but in order to provide a stronger demonstration it is desirable to run a short version with a different sample. To this end, in Experiment 2 we create two candidate versions of a short form SLSA and investigate the extent to which they are consistent with the full SLSA.

2.6 Methods

Two sets of 6 SLSA trials were used in this experiment. These sets were selected from the 16 trials in the full version (Experiment 1). We examined the correlations between SI in the original 16-trial set and SI in each subset of 6 trials. Set 1 was selected as the set of 6 trials with the strongest correlation between SI in the 6-trial set and SI in the original 16-trial set ($r = +0.94$). However, this set contained two trials that had the same physical layout and were only different because one featured reversed start-to-goal and goal-to-start paths relative to the other. To ensure this did not impact the results, Set 2 was selected on the basis of having the strongest correlation between SI in the 6-trial set and SI in the original 16-trial set, but with no trials using the same physical layout ($r = +.92$). Set 1 and Set 2 shared 4 of their 6 trials.

2.6.1 Participants

A total of 41 (21 female, mean age: 19.9 years, age range: 17-24 years) Johns Hopkins University students participated in exchange for extra credit in introductory psychology courses.

2.6.2 Materials and Procedure

Participants completed one of two versions of the 6-trial SLSA and a block of paper and pencil questionnaires including the Santa Barbara Sense of Direction scale, Questionnaire on Spatial Representation, and Mental Rotation Test. The Spatial Perspective Test was also

included, but we observed the same issues as in Experiment 1 and thus did not report results from the measure. Each version of the SLSA was identical except for the order of trials. Presentation was counterbalanced across participants. Questionnaires were presented in a random order. Order of presentation of the SLSA and the block of questionnaires was counterbalanced across participants. All materials were the same as in Experiment 1, except for the number of trials in the SLSA.

2.7 Results & Discussion

The structure of the results is as follows. First, we review the summary data and investigate for any possible gender differences. Next, we investigate how the performance-based measures from the 6-trial SLSA relate to self-report and spatial skill measures, with the expectation that these relationships will be the same as the ones found for the full version. Finally we present Monte Carlo simulations to understand whether the distributions of SI are stable in the 6-trial version of the SLSA.

2.7.1 Summary Data

As in Experiment 1, we first examined the descriptive statistics for all measures. In addition, we ran a comparison of males and females and Set 1 and Set 2 to assess possible gender or set differences. Table 5 shows the summary data and comparisons of gender differences. Using 2x2 ANOVAs, we observed the typical male advantage on the Mental Rotation Test, $F(1,40) = 5.75, p < 0.05$. Males also rated themselves more highly on the Santa Barbara Sense of Direction Scale, $F(1,40) = 4.49, p < 0.05$. Finally, there was a difference between sets, such that participants in Set 1 rated themselves higher on the Questionnaire on Spatial Representation-Landmark scale than participants in Set 2. No other significant gender or set differences were observed.

Table 5. Means and standard deviations for all measures in Experiment 2. Means and t-tests compare females and males.

	Overall	Females	Males	F vs. M
	Mean (s)	Mean (s)	Mean (s)	t-test
SLSA % Complete	0.91 (0.11)	0.88 (0.12)	0.93 (0.08)	t(39) = 1.62 p = 0.114
SLSA SI	0.59 (0.37)	0.62 (0.34)	0.55 (0.40)	t(39) = 0.66 p = 0.511
Santa Barbara Sense of Direction	62.29 (14.42)	57.52 (15.85)	67.25 (11.05)	t(39) = 2.27 p = 0.029
QSR-Style	-0.12 (2.33)	-0.24 (2.70)	0.00 (1.92)	t(39) = 0.32 p = 0.748
Mental Rotation Test	22.73 (9.68)	19.24 (8.83)	26.40 (9.37)	t(39) = 2.52 p = 0.016
Spatial Perspective Taking	153.96 (17.43)	152.31 (17.76)	155.68 (17.35)	t(39) = 0.61 p = 0.542

SLSA success rate, SI, and QSR-Style were calculated in the same manner as in Experiment 1. First, we examined the correlations between the self-report individual differences measures and the spatial skill measures (Table 6). A positive correlation between the Mental Rotation Test and Santa Barbara Sense of Direction Scale, $r = +.32$, was also observed.

Before proceeding on to the target questions of interest, we examined whether the correlations between measures differed as a function of which set of 6 trials participants received. No such correlations were observed, which is consistent with the two sets of trials measuring the same variance.

In order to further investigate the reliability of 6-trial versions of the SLSA, we next explore the extent to which the relationships between measures from the SLSA and self-report

Table 6. Correlations (r) among the individual differences test broken down by dataset and gender in Experiment 2.

Overall			
	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Santa Barbara Sense of Direction	+.08	+.32 †	+.21
QSR-Style	-	+.24	+.04
Mental Rotation Test	-	-	+.40 †
Female			
	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Santa Barbara Sense of Direction	+.04	+.38	+.25
QSR-Style	-	-.04	-.14
Mental Rotation Test	-	-	+.27
Male			
	QSR-Style	Mental Rotation Test	Spatial Perspective Taking
Santa Barbara Sense of Direction	+.40	-.01	-.24
QSR-Style	-	+.65 ★*	+.30
Mental Rotation Test	-	-	+.52 †

† p < 0.05 uncorrected.

★ p < 0.05 corrected for relevant subset of 6 correlations.

★* p < 0.05 corrected for all 18 correlations in a given dataset (Full or Reduced).

and spatial skills measures resemble those found in Experiment 1.

2.7.2 Success Rate

2.7.2.1 Self-report measures.

2.7.2.1.1 Santa Barbara Sense of Direction. As shown in Table 7, SLSA success rates were not correlated with Santa Barbara Sense of Direction scores, $r = -.05$. Although this correlation was numerically stronger in males than females, the difference was not significant, $p > 0.64$. These results replicate the findings from Experiment 1 that SLSA success rate and Santa Barbara Sense of Direction scores were not significantly correlated, providing support for the 6-trial versions of the SLSA capturing the same individual differences as the full version.

2.7.2.1.2 QSR-Style. SLSA success rates were not correlated with QSR-Style, $r = -.12$. A Fisher's z revealed no significant gender differences, $p > 0.19$. These results replicate the finding from Experiment 1, providing support for the 6-trial versions of the SLSA capturing the same individual differences as the full version.

2.7.2.2 Mental Rotation Test. Mental Rotation Test scores were positively correlated with SLSA success rates, $r = +.35$. Although this correlation was numerically larger for males than for females, a Fisher's z revealed no significant difference, $p > 0.68$. These results replicate Experiment 1. Replicating this relationship is consistent with the 6-trial SLSA capturing the same variance as the full version.

In summary, if the short form SLSA is reliably measuring the same constructs at the full version, we would expect that SLSA success rates for both versions would exhibit the same relationships with the Santa Barbara Sense of Direction Scale, QSR-Style and Mental Rotation Test. This was the case for all measures. These results are consistent with the 6-trial SLSA being a reliable measure of navigational prowess, albeit with a limited range.

2.7.3 Solution Index

2.7.3.1 Self-report measures.

2.7.3.1.1 Santa Barbara Sense of Direction. As shown in Table 7, SLSA SI was not correlated with Santa Barbara Sense of Direction scores, $r = +.19$. A Fisher's z revealed no gender differences, $p > 0.87$. These results replicate Experiment 1, which is consistent with the 6-trial versions of the SLSA measuring the same individual differences as the full version.

2.7.3.1.2 QSR-Style. SLSA SI was not correlated with QSR-Style, $r = +.09$. A Fisher's z revealed no gender differences, $p > 0.19$. These results replicate Experiment 1, which is consistent with the 6-trial versions of the SLSA measuring the same individual differences as the full version.

2.7.3.2 Mental Rotation Test. Mental Rotation Test scores positively correlated with SLSA SI, $r = +.32$. Although this correlation was numerically larger for males than for females, a Fisher's z revealed that these correlations were not significantly different, $p > 0.47$. This fails to replicate the finding from Experiment 1 that Mental Rotation Test scores were not correlated with SLSA SI. This failure to replicate does not provide support for the 6-trial SLSA measuring the same individual differences as the full version. The results from the Monte Carlo simulations in Experiment 1 indicate that the extent to which mental rotation ability is related to success is a function of both the kinds of solutions an individual used and the set of environments they learned. It may be the case, then, that this relationship is an artifact of the specific set of trials used. This indicates that, although the 6-trial SLSA appears to be capturing the same individual differences as the full version, it may be important to use more trials when relationships of interest vary depending on the exact structure of the environment.

2.7.4 Comparison of Experiment 1 and Experiment 2

In order to be sure that the 6-trial versions of the SLSA were capturing the same individual differences as the full version, we need to be sure that the distributions of SI produced by these measures are not different. To do this, we conducted a series of Monte Carlo simulations. For each Set, we performed a Monte Carlo simulation in which SI was calculated

Table 7. Correlations (<i>r</i>) between each dependent measure from the navigation tests and each of the individual differences measures broken down by dataset and gender in Experiment 2.					
Overall					
		Santa Barbara Sense of Direction	QSR- Style	Mental Rotation Test	Spatial Perspective Taking
SLSA	% Complete	-.05	-.12	+.35 †	-.05
	SI	+.19	+.09	+.32 †	-.10
Female					
		Santa Barbara Sense of Direction	QSR- Style	Mental Rotation Test	Spatial Perspective Taking
SLSA	% Complete	-.10	-.27	+.21	-.32
	SI	+.27	-.01	+.47 †	-.29
Male					
		Santa Barbara Sense of Direction	QSR- Style	Mental Rotation Test	Spatial Perspective Taking
SLSA	% Complete	-.25	+.16	+.40	+.28
	SI	+.22	+.23	+.34	+.08
† $p < 0.05$ uncorrected. ✱ $p < 0.05$ corrected for relevant subset of 4 correlations for each dependent measure within. ✱* $p < 0.05$ corrected for all 24 correlations presented here.					

from the Experiment 1 data using only the 6 trials used in that Set for n subjects, where n is the number of participants who completed that Set in Experiment 2. For each Set, 10,000 such permutations were calculated and compiled to create an idealized distribution of the data. The shapes of these distributions were then compared to the distributions from Experiment 2. Neither Set 1, $D = 0.11$, $p > 0.8$, nor Set 2, $D = 0.29$, $p > 0.8$ differed significantly from the idealized distributions. This supports the assertion that the 6-trial versions of the SLSA are measuring SI in the same way as the full version, thus providing support for the short version as a reliable measure of navigational style.

With the abbreviated version of the SLSA, we were able to replicate most of the results from Experiment 1, suggesting that the shortened format may be sufficient as a behavioral measure of navigational success and style. Furthermore, distributions of SI from the short version did not differ from idealized distributions taken from the full version. This provides support for the reliability of measurement of how an individual spontaneously navigates with only 6 trials. As such, the short SLSA may provide a valuable tool for measuring spatial learning style as a part of a battery of individual differences measures.

2.8 Discussion

2.8.1 Do Self-Report Measures Correspond with Performance-Based Measures?

Previous research on individual differences in human navigation and spatial learning has often relied on self-report techniques to collect data. These methods can be invaluable in some situations, but they come with strong assumptions about the nature of the construct being investigated. Self-report measures require one to have some metacognitive knowledge of the processes being investigated, and are inherently recollective and can therefore be biased. These assumptions may be true for some constructs, but not necessarily for navigation.

Supporting the idea that these assumptions are not true for navigation, we found weak, nonsignificant relationships between self-reported sense of direction and success on performance-based tasks, and between self-reported preference for environmental information and how a participant navigates on these tasks. This is in conflict with the results from Furman et al., 2014. This discrepancy demonstrates that data from these self-report measures are likely telling an incomplete story about how individuals navigate. The current results highlight the need for careful examination of the assumptions used when investigating navigation and spatial learning and the need for considering subjective preferences and behavioral biases separately.

2.8.2 Validity of the SLSA

Although performance-based measures have been developed, these methods remain time intensive and relatively inflexible in terms of the possible manipulations that can be performed because they require massed encoding of one large environment prior to test. This poses a barrier to researchers who wish to supplement or replace self-report measures with performance-based ones. The SLSA fills this void by providing a complementary performance-based measure of how individuals learn and navigate through an environment that is flexible and scalable.

The results from this study are consistent with the SLSA being a valid and reliable measure of navigational style. First and foremost, its measures of success and SI were related to those of the DSP, indicating that they are capturing some of the same variance. The two measures also, by and large, had the same relationships with self-report and spatial skills measures. The exception to this was with mental rotation ability, which likely indicates that mental rotation ability is most critically engaged in the early moments of spatial learning. Finally, using Monte Carlo simulations, we have an indication that the results from the measures from the SLSA are relatively stable and can be obtained using as few as 6 trials. Overall, this

provides strong support for the SLSA as a valid and reliable performance-based measure of navigational style.

By using a single, brief exposure to each environment, the SLSA is capable of letting researchers vary environmental features in a way that isn't possible with previous measures. It is also capable of being scaled down to a small number of trials, as evidenced by the stability of SI in the 6-trial versions and measures from the 6-trial SLSA replicating the patterns among 16-trial SLSA measures and other tasks. The ability to scale the task makes it appropriate for use in a battery of assessments. Using 6 trials, one can obtain a stable measure of spatial learning style in approximately 15 minutes. Thus the SLSA can be an excellent tool in experiments in which time is at a premium or the experiment requires manipulation of environmental features. Such a modular measure of spatial learning style could prove useful in other domains as well. For example, the SLSA could be used as a training tool by requiring participants to use a particular strategy on given trials.

2.8.3 Spatial Skills and Successful Navigation

Previous research has demonstrated the importance of spatial skills for success in various navigationally relevant tasks (e.g. Allen et al., 1996; Fields & Shelton, 2006; Hegarty et al., 2006; Kozhevnikov et al., 2006). Here we made a first pass at exploring how these spatial skills interact with one's spatial learning style. We predicted that spatial skills would be particularly important for successful navigation when one is using an effortful, global structure strategy. Although this was true in Experiment 1, Monte Carlo analyses revealed that this is an artifact of the particular trial list used. Instead of spatial skills being related to success using a particular strategy, this relationship appears to be dependent on which environments a participant learned.

This could occur because the layouts of some of the environments were particularly conducive to using mental rotation or was sufficiently complex to require relatively more processing.

Thus spatial skills may become important for success with a given strategy when particular environmental features are present or when information from the environment requires additional processing to be consistent with a particular strategy. Additionally, the range of success rates was extremely small, which limits the conclusions that can be drawn from this. In sum, these results underscore the idea that individual differences, one's representation of the environment, and features of the environment all interact successful navigation (Carlson et al., 2010) and motivates the need to investigate the relationship between mental rotation and spatial skills in a more systematic manner.

2.8.4 Conclusion

Taken together, these results begin to shape a picture of what makes a person a successful navigator. Navigation is not a unitary ability, but rather the interaction between one's preferences, skills, and the environment they are navigating in. A person who can easily make detours from their route by using distant landmarks may struggle when they are not present. Similarly, a person without strong spatial skills may excel at navigation in repetitive, grid-like environments, but struggle when the environment is irregular and requires more constant updating of direction. Although the lack of range in success rates makes such conclusions tentative, these experiments add to the case that spatial skills and the selection of solutions during navigation may be predictors of success when navigating.

Finally, and perhaps most critically, these experiments provide support for the SLSA as a valid and reliable performance-based measure of the selection of solutions during navigation. This measure encapsulates learning and test into each trial, allowing for the use of multiple

environments, varying task instructions between trials, and a scalable number of trials to suit the present experimental purpose. This perfectly satisfies the need stated in Chapter 1 for a measure of selection of solutions. Given the one-shot nature of these trials, participants can be instructed to use a specific kind of solution after the learning phase without fear of previous trials in the environment contaminating that present trial. This satisfies the need for a measure of capacity for solution use. Finally, previous pilot studies have indicated that larger environments and environments which appear to be embedded in a larger maze lead to a wider range of success rates (Nelligan & Shelton, unpublished data). These features could easily be added to the SLSA paradigm to satisfy the need for a measure of navigational success. In summary, the SLSA, with minor modifications, is capable of satisfying all of the methodological needs for a more thorough study of successful navigation.

Chapter 3: Successful Navigation

3.1 Introduction

Try to recall the last time you got lost when going from one place to another. Such experiences are almost universally negative – one feels confused and irritated, perhaps even scared by the area they have inadvertently wandered into. Getting lost is certainly an experience we try to avoid. But how often do these experiences occur? Some people seem to almost never be lost when they navigate and may even take for granted the ability they have to reliably make it to their destination, whereas for other people these experiences are quite common. They may struggle to find their way and become reliant on GPS or help from others to navigate through the world. This difference between individuals is even more striking given the ubiquitous need to navigate - when was the last time you *didn't* need to go from one location to another in your day? Even in most of our homes, we have to move room to room. In this experiment, we set out to better understand which factors determine why some individuals are more successful at navigating than others.

What has been remarkable about previous studies of navigation is the extent to which, implicitly or explicitly, they have focused on the importance of learning a lot about the environment. Studies of navigational preferences have focused on preference for kinds of environmental information (e.g. Lawton, 1994; Pazzaglia & DeBeni, 2001). Studies have used self-reported “sense of direction”, one’s opinion of how well they navigate, as a proxy for how often one gets to their destination (e.g. Hegarty et al., 2002; Prestopnik & Roskos-Ewoldsen, 2000; Weisberg et al., 2014). But the most common measure of “sense of direction”, the Santa Barbara Sense of Direction Scale (Hegarty et al., 2002), includes items biased towards environmental learning, such as “I am very good at judging distances” or “I don’t have a very

good mental map of my environment”. Many other studies use measures such as estimating distances between locations (Allen et al., 1996; Hegarty et al., 2006; Lawton 1994), estimating the direction from one object to another (Allen et al., 1996; Hegarty et al., 2006; Ishikawa & Montello, 2006; Lawton 1994; Weisberg et al., 2014), drawing maps on an environment (Allen et al., 1996; Coluccia et al., 2007; Hegarty et al., 2006) or being able to find novel shortcuts in an environment (Allen et al., 1996; Mengue-Topio et al., 2011; Weisberg et al., 2014) as proxies for how well one navigates.

Without a doubt, these matters are interesting and important to a full understanding of human navigation. There is certainly a logical case to be made that these abilities may contribute to how successful one is when they navigate. Knowing more about an environment may mean that one has more information to use when trying to figure out the best way to navigate through it and thus could confer an advantage. But this does not have to be the case. Recent studies have begun emphasizing that there are multiple kinds of solutions one can use to solve a navigation problem. Some of these solutions involve using one’s knowledge of the structure of the environment to reason out a path, but others involve using familiar or habitual sequences of events to navigate (Furman et al., 2014; Marchette et al., 2010). The later class of solutions does not necessarily require a thorough knowledge of the environment in order to be effective. Something as sparse as a series of stimulus-response associations could be enough to support this kind of solution. If this is the case, the current measures focusing on one’s knowledge of the environment would not be effective at capturing success with these solutions.

As an example, consider two studies in which participants learned an environment, either by being driven through it several times (Ishikawa & Montello, 2006) or by navigating through it virtually (Weisberg et al., 2014). In both of these studies, there was a subset of participants that

showed no improvement in their knowledge of the environment; in fact, these participants seemed to not learn anything about the environment at all. This was particularly vexing in the Weisberg et al. study because these participants were able to navigate through the environment, but were unable to perform well on any measure of knowledge of the environment, such as distance and direction judgments or map drawing. In terms of their goal of navigating from one location to another, they were quite successful, but the measures used did not reflect this.

This is illustrative of a larger question – what is the goal of navigation? If the goal is to obtain information about your environment so that you can use it later, then these previous measures of environmental learning are capturing it well. But this seems incomplete. If I were to drive from an unfamiliar city’s airport to my hotel, but have absolutely no knowledge of the layout of the city afterwards, am I really being unsuccessful? My goal was to get from one location to another and I accomplished exactly that, but in terms of learning about the environment I have been quite unsuccessful. It remains an open possibility that the implicit reduction of successful navigation to good environmental learning is leaving us with an incomplete story about how we navigate. In order to begin to clarify this, in this experiment we investigate the simpler question – *what factors predict who will get to their destination more often?*

Although previous research has not focused on this question, we can use factors that have been shown to relate to environmental learning as a starting point for factors that may relate to successful navigation. Broadly speaking, these can be broken into three categories: the selection of solutions, the capacity for solutions, and spatial skills. These were covered in more detail in Chapter 1 but are briefly recapped here for reference.

3.1.1 Selecting appropriate solutions. Moving from ideas of good environmental learning to successful navigation allows for the possibility that there are multiple ways to be successful. This emphasis on multiple kinds of solutions to navigation problems allows for new possibilities as to what may contribute to someone being successful. When navigating in virtual environments, individuals vary in the mixture of solutions they use – in fact individuals fall at all points of a continuum of the relative use of familiar solutions (solutions that one knows from experience will be successful) and novel solutions, that had to be reasoned out (Furman et al., 2014; Marchette et al., 2010; for review, see Shelton, et al. 2013). If individuals differ in the kinds of solutions they use in these tasks, they must be somehow adjudicating between different solutions.

Thus it could be the case that individual differences in how solutions are selected contribute to how successful an individual ultimately is when navigating. For example, the current literature on navigation might suggest that being able to take novel shortcuts is indicative of being “better”, but little is known about whether one solution might generally lead to more successful navigation than another. More likely, individuals who can correctly adjudicate among possible solutions might be more successful than those that stick to one or another (e.g., Shelton, unpublished preliminary data), but the relationship between solution use and success rate has yet to be systematically examined. Such conjecture suggests there are two different ways to think about solution use that might have different contributions; the strength of subjective preference for different solutions and the propensity to use a variety of solutions when navigating.

3.1.1.1 Preference and propensity for specific solutions. Individuals differ in their reported preference for different kinds of solutions (e.g. Marchette et al., 2010; Pazzaglia & DeBeni, 2001). There is some evidence that suggests that a preference for learning the global

structure of an environment, which underlies the ability to identify correct novel pathways, is indirectly related to navigation performance. Self-reported preference for this kind of learning is related to self-reported “sense of direction”, or how good one thinks they are when navigating (Prestopnik & Roskos-Ewoldsen, 2000), which is in turn predictive of how accurately one estimates distances and directions in an environment (Hegarty et al., 2002). In the other direction, lower preference for this kind of global structure information is associated with higher rates of anxiety in navigational situations, and such anxiety is negatively associated with accuracy on measures of distance and direction estimation (Lawton, 1994).

It is important to note that, as a field, we are still elucidating the extent to which these self-reports reflect behavior. For example, there are countless examples of processes that are implicit in nature (e.g. Greenwald et al., 1998; Milner et al., 1968; Nisbett & Wilson, 1977; Schacter, 1987; Squire, 1992). If such non-declarative processes contribute to navigation, then self-reports are unlikely to accurately or completely capture these aspects of behavior. One study has found that self-reported preferences correlated with behavior in a virtual navigation task (Furman et al., 2014), but this finding needs to be replicated in order to draw a definitive conclusion. Given that observed biases and self-reported preferences may pick up on different constructs, both will be investigated here.

In summary, self-reported preference for global structure information has been indirectly related to how well an individual understands the spatial relationships between objects in an environment and there is preliminary evidence that these self-reported preferences may be indicative of observed behavior. Thus we will measure both self-reported preferences and observed behavioral biases and predict that both preferences and biases for global structure information will be related to successful navigation in this study.

3.1.1.2 Spontaneous flexibility of solution selection. The preceding section is heavily driven by the idea that one solution might be better or worse than another. However, it is possible that one's preference or biases for a specific kind of solution is not critical to success. Instead, it may be the extent to which one switches among solutions in different situations. The (indirect) evidence presented above indicates that a self-reported preference for one kind of solution may confer an advantage in some navigationally-relevant tasks. This could be because individuals who self-report a preference for global structure information are *able* to use novel solutions in some situations in addition to other kinds of solutions, which might reflect having more potential solutions available when selecting what will work for a given situation. In this way, it may not be the preference itself that contributes to success, but the ability to overcome one's preference and use a variety of solutions in different situations that is critical to success.

We might also expect that, irrespective of reported preference or observed bias, the ability to shift solutions in response to different navigational challenges might be a better predictor of success than any aspect of reported preference. For the sake of brevity, we will refer to this ability to switch solutions as flexibility in solution use. This predicts two possible scenarios for how solution selection might be related to success. First, as described above, it may be that preference for more global structure information is indicative of better flexibility in solution use. In such a case, preference and measures of flexibility in solution use will predict success, but will not have independent contributions to it. Alternatively, it may be that flexibility in solution use is independent of reported preferences (which may or may not tell us anything about what people *can* do). If so, then we would expect a greater contribution of flexibility in solution use to predicting success.

3.1.1.3 Summary. The shift from focusing on learning the structure of the environment to focusing on successful navigation opens the possibility that the kinds of solutions one uses may influence whether they get to their destination. Previous research has related self-reported preference for global structure information, which is necessary for successfully using novel solutions, to better environmental structure learning and indirectly to successful navigation. To the extent that good environmental structure learning is indicative of successful navigation, we would expect to find that measures of preference and bias for learning global structure information are predictive of successful navigation. Not finding this would indicate that, at the least, preferences and biases indicative of good environmental structure learning are not necessary to be successful and that other kinds of solutions, such as relying on familiar paths, may be just as effective.

Another possibility is that being able to use multiple solutions in any given situation may confer an advantage when navigating and that spontaneously using a variety of different solutions when navigating is indicative of this ability. If this is the case, we would expect to find that measures of flexibility in solution use predict success. Not finding this would be consistent with views that one kind of solution is better suited to success than others or that it is one's capacity to use particular kinds of solutions that best predicts success.

3.1.2 Capacity for specific solutions. In real-world navigation, it is rare that there is only one way a person can go and be successful – there are typically multiple solutions to a navigation problem that will allow a person to get to his or her destination. Having already discussed variability in the selection of these solutions, we can now turn our attention to a second aspect of them – how well a person can use a given kind of solution. Previous research has identified three categories of solutions to describe the different ways one can navigate: novel solutions,

familiar solutions, and reversal solutions, with the first two being the predominant and more thoroughly studied solutions (e.g. Furman et al., 2014; Marchette et al., 2010). Here we describe each of these kinds of solutions and detail what is known about how the ability to use them relates to navigation. Much of the previous work on this topic has centered on subjective preference for different solutions rather than one's ability to use a specific kind of solution.

Novel solutions involve identifying a previously untraveled path using one's knowledge of the environment. For example, if there was construction on some of the streets you usually use to drive home, you could use your knowledge of the neighborhood to find a detour, even if you have never driven that exact route before. As described above, there is some evidence that connects a preference for learning the global structure of an environment, which underlies the ability to identify correct novel pathways, to navigation performance. Briefly, this preference has been related higher self-reported "sense of direction" (Prestopnik & Roskos-Ewoldsen, 2000), one's subjective evaluation of their navigation abilities, which in turn correlates with performance on distance and direction estimations in real and virtual environments (Hegarty et al., 2006). This preference for information underling novel solutions has also been related to less anxiety about navigating and such anxiety is related to worse performance at distance and direction estimates (Lawton, 1994). One's self-reported preference for global structure information, which underlies preference for using novel solutions, thus relates indirectly to constructs which may be predictive of successful navigation. However, the relationship between one's actual ability to execute these solutions and their overall success when navigating has not yet been examined.

Familiar solutions involve following a previously navigated path. For example, many people use the same route every day to go to work in the morning. In fact, one might even find

themselves absentmindedly driving down that same route on a Saturday before realizing that their destination is not work. Preference for familiar solutions has been previously investigated, but unlike preference for novel solution, no relationships were found with sense of direction (Prestopnik & Roskos-Ewoldsen, 2000) or spatial anxiety (Lawton, 1994). Although there is no connection between preference for familiar solutions and navigation, the possibility remains that how proficient someone is at these kinds of solutions may relate to their overall success when navigating, particularly because most previous studies of navigation have used explicit judgments of spatial information which may not be indicative of familiar solutions.

Reversal solutions involve using a familiar solution, but in the opposite direction of how it was originally experienced. For example, an invited speaker may be led across campus for a meeting with a colleague, but when the meeting is over their guide does not show up to walk them back across campus. The speaker could use knowledge of the path they used to get there, but would have to manipulate this information because they never traveled the *exact* path they are attempting to use. Relative to novel and familiar solutions, much less is known about reversal solutions. One study found that participants who were good at using reversal solutions were also good at using both familiar and novel solutions (Shelton et al., in prep). It is important to note that in this study, participants were required to use a particular solution on each trial in order for that trial to be counted as successful, so the results are about capacity for the solution rather than selection. This result may be an indication that reversals represent a hybrid of both reversal and familiar solutions, in that a person is taking a familiar solution and manipulating it to create a novel one. Thus how the ability to use reversal solutions related to overall success when navigating remains an open question.

As illustrated by the evidence reviewed above, previous research has focused on examining subjective preference for different kinds of information or solutions rather than examining how the capability to use each kind of solution relates to successful navigation. Therefore, in order to better understand how the ability to perform these solutions may relate to one's overall ability to successfully navigate when any solution is feasible, it is ideal to measure participants' observed ability to use these solutions. Doing this, in conjunction with measures of preference and bias in solution use, will allow us to understand how the relative contributions of capacity for specific solutions and propensity to use those solutions.

Finding that only the capacity for novel solutions is predictive of successful navigation would be consistent with previous research which has equated successful navigation with good environmental structure learning. Finding that multiple kinds of capacities predict success would indicate that not only has that view been incomplete, but that there are multiple ways for one to be successful when navigating. On the opposite end of the spectrum, finding that none of these capacities relate to success could be an indication that it is not how good one is with a particular solution that allows them to get to their goal location, but some other factor, for example the solutions they tend to use.

3.1.3 Spatial Skills. Spatial skills are a class of abilities that allow us to imagine and reason about the objects and the relationships among objects in the world. We focus on two such skills here—mental rotation and spatial working memory. Although spatial perspective taking was discussed in Chapter 1, it was not included in this experiment because of the methodological concerns with the measure described in Chapter 2. Both mental rotation ability and spatial working memory have been shown to relate to some aspect of environmental learning, as

described in more detail in Chapter 1, but none have been directly related to success when navigating in a situation in which multiple solutions are possible.

Briefly, mental rotation is the ability to imagine an object rotating in space (Vandenberg & Kuse, 1976). For example, one might be packing the trunk of their car to go on a trip and need to imagine their suitcase at different orientations to determine where it will fit in the already full space. In navigation, better mental rotation ability has been associated with greater accuracy at correctly tracing previously navigated paths onto a 2-dimensional map (Kozhevnikov, Motes, Rasch, & Blajenkova, 2006) and remembering and navigating to hidden locations in a virtual maze (Astur, Tropp, Sava, Constable, & Markus, 2004), suggesting that thinking about a space more globally may engage mental rotation processes. Consistent with this relationship, Shelton and Gabrieli (2004) found that brain activation in regions associated with spatial learning was correlated with Mental Rotation Test scores in conditions that required utilizing global structure.

The next spatial ability, spatial working memory, is the ability to maintain and manipulate spatial information in memory (Shah & Miyake, 1996). For example, a person might turn off the lights in a hotel room at night and need to walk through the room in the dark in order to go to bed. To do this without running into furniture, he/she would need to hold the location of the furniture in the room in working memory in order to determine the open walkways. Higher spatial working memory capacity has been correlated with higher accuracy at estimating distances (Allen et al., 1992; Hegarty et al., 2006), estimating directions (Hegarty et al., 2006), and drawing maps (Allen et al., 1996), suggesting that greater capacity for spatial information is related to greater proficiency at learning of the spatial relations between locations in an environment. Moreover, when spatial working memory was taxed by requiring participants to do a secondary task, individuals committed more errors when navigating (Coluccia et al., 2007;

Garden et al., 2002), suggesting that some aspects of spatial working memory are engaged during navigation.

In summary, mental rotation and spatial working memory appear to be associated with how well one learns the relationships among objects in an environment and the structure of the environment. These aspects of environmental learning could be critical to how successful a person tends to be when they navigate, particularly a person who uses solutions involving the global structure of the environment. But a direct connection between these spatial skills and *successful* navigation has not been made. Thus, although previous evidence suggests that spatial skills are relevant to navigation, whether these spatial skills can predict how successfully one tends to navigate remains an open question.

Finding unique contributions of spatial skills to navigational success would indicate that the act of navigating successfully is engaging spatial skills above and beyond their use by any specific capacity for using a solution. Depending on the relationships between other constructs, this may indicate that selecting an appropriate solution engages spatial skills. Alternatively, it is possible that spatial skills are related to navigational success, but are not unique predictors. This would indicate that spatial skills are contributing to other processes, which are in turn directly predicting success. For example, the literature suggests that spatial skills are particularly important for learning the global structure of an environment. Thus it could be the case that spatial skills contribute to the capacity to use novel solutions, which relies on learning the global structure of an environment, and that capacity in turn uniquely predicts success. Finally, it could be the case that spatial skills have no relationship with successful navigation. Given previous research demonstrating a relationship between spatial skills and other aspects of navigation, it is unlikely that spatial skills simply aren't engaged when navigating. Thus this would likely

indicate that either there are solutions one can use which do not require high spatial abilities to be successful, or that higher spatial abilities are not critical to success with any solutions.

3.1.4 Present Study. In order to carry out this experiment, we first need experimental paradigms that can measure how individuals navigate in situations where multiple solutions are possible. These paradigms also need to be scalable in size to accommodate the demands of each measure and use different environments in order to minimize overlearning or cross-contamination between measures. The Spatial Learning Styles Assessment (SLSA; Chapter 2) fits all of these criteria. Now that we have a reliable methodology, we can directly address the question, *which factors contribute to individual differences in successful navigation?* This was done by using measures of spatial skills, preference and bias for using different kinds of solutions, capacity to use different kinds of solutions when explicitly required to, and a measure of flexibility of solution use. With the exception of the spatial skills and preference measures, all of these were created using modifications of the basic SLSA methodology. These modifications are outlined below.

3.2 Methods

3.2.1 Participants. 107 Johns Hopkins University undergraduate students participated and were compensated for their time with course credit. Of these, 7 failed to complete the second part of the study and were removed. Data from 1 participant was removed due to noncompliance on the navigation tasks. Thus data from 99 participants (52 female) were analyzed.

3.2.2 Materials.

3.2.2.1 Spatial Learning Styles Assessment (SLSA). This task consisted of 10 different 9 × 9 virtual environment (VE) mazes (constructed in Portal; www.valvesoftware.com).

Environments differed in terms of the arrangement of hallways and the textures of the walls and floor. Each VE contained 3 paths which led to the goal object: a start-to-goal path, a goal-to-start path, and a novel shortcut that was shorter than the other two paths, visible during the initial travel from start to goal and back, but never directly experienced by the participant. Half of the trials used the same physical structure as another trial except that the start-to-goal and goal-to-start paths were reversed and they had different wall and floor textures.

As described in Experiment 2, 6 trials are sufficient to obtain stable data from this measure, but because data from this measure were analyzed using correlations additional trials were included to ensure a sufficient amount of variability in the data.

On each trial, the encoding phase began with the participant being guided along the start-to-goal path. Once at the goal, the participants viewed the goal object for 2 seconds and were then led back to the start location along a different path—the goal-to-start path. At the start location, the navigation portion of the trial began. The participant was rotated to face the same direction faced at the beginning of the encoding phase and was instructed to navigate to the goal object. During navigation, the participant was given 37 seconds to reach the goal object before a buzzer sound was played and the trial was considered unsuccessful. Participants initially completed one practice trial to familiarize them with using the arrow keys on the keyboard to navigate. The trial order for the 10 test trials was determined by creating 2 random sets of all trials and randomly assigning half of the participants to each order.

On each trial, we record the specific path navigated and whether or not the target was reached before the time limit. From these values, we are able to calculate an evaluation of the solution used. We quantified solution use in terms of the proportion of successful trials on which the participant used the familiar path (start-to-goal), a novel shortcut, or a reversal (goal-to-start,

which was only experienced in the opposite direction). We also calculated the solution index (SI) that has been used previously to quantify solution use. SI was calculated by taking all trials for which the solution could be classified as either familiar path use or novel shortcut use, and calculating the proportion of those trials for which the participant used the novel shortcut:

$$\frac{\# \text{ shortcuts}}{(\# \text{ shortcuts} + \# \text{ familiar paths})}$$

Measuring SI in this way is important because it has been extensively validated and grounded in the underlying neurobiology using the DSP (Marchette et al., 2010). However, this obviously does not account for the use of reversals. To account for this kind of solution, we also examined participants' propensity to use reversals separately from their SI.

3.2.2.2 Success Rate Assessment. Although the SLSA is a reliable measure of propensity to use different kinds of solutions, participants tended to have extremely high success rates (~90% mean success rate). This is advantageous for being able to determine rates of solution use, but it limits the range over which we can use other variables to predict success. We developed a more difficult version of the navigational tasks used in the SLSA, the Success Rate Assessment, to overcome this limitation. From pilot testing of the paradigm prior to Experiments 1 & 2, we found that using a larger environment (10 x 10) and embedding the environment within a much larger maze, rather than having an external wall, resulted in a wider range of success rates (~64% mean success rate, ~12% standard deviation). This is ideal for a task intended to measure variability in navigational success using a format parallel to the SLSA.

Based on this pilot work, the Success Rate Assessment environments were similar to the SLSA, but with the following critical exceptions. The environments were embedded in a larger maze such that participants were unable to leave the 10 x 10 area, but could see the maze continue well beyond that area. Thus they appeared to be in a much larger maze, but the space

they can actually navigate was restricted. If they attempted to leave the 10 x 10 area, they were stopped, turned 180°, and shown a message of “Wrong Way”. Following the same logic that was used for the SLSA, this task was comprised of 10 trials in order to allow for a more nuanced look at success rate. Participants had 45 seconds to reach the goal location. The time limit was longer than in the SLSA because the larger environments contain longer paths, and thus participants needed more time to traverse them. Trial order was determined by creating 2 random sets of all trials and assigning those 2 sets across participants, such that each order was equally distributed. As in the SLSA, familiar, novel, and reversal solutions were available. Success rate was the critical measure from this task and was calculated as the percent of trials in which the participant successfully found the goal.

3.2.2.3 Required Solutions Task. The Required Solutions Task was used to measure an individual’s capacity for different kinds of solutions. It was modeled after a similar task developed on the DSP (Shelton, Marchette, and Brockman, in prep). Whereas the standard task measures what people choose to do, this task was designed to determine participants’ capacity to use familiar, novel, and reversal solutions on demand. It followed the same procedure and design as the SLSA with the following exceptions. First, instead of giving participants the choice of which path they want to take, there were instructions immediately following the encoding period on each trial that informed the participant to take a specific path to the goal location: the familiar path, a novel path, or the reversal.

Based on the trial type, the paths available to the participant were constrained such that the participant could stray onto the other possible paths for up to 2 units of path length before the path would be blocked. This provided sufficient distance to accurately record wrong path attempts without allowing the participant to spend too much time on a single wrong path. For

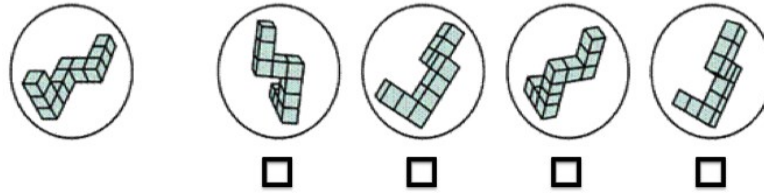
any given trial type, the required path was the shortest possible on 50% of trials. As such, rather than asking people to find a shortcut or use the familiar path, we asked them to explicitly decide to use either the familiar path (as is or in reverse) or a path they knew to be novel (even if it is longer). This was done to eliminate the heuristic of “learn the shortest path” and ensure a more accurate measurement of the underlying knowledge about the environment. Each permutation was presented 6 times for a total of 36 trials. Trial order was determined by creating 2 random sets of all trials and assigning those 2 sets across participants, such that each order will be equally distributed. Success rate for each required solution type was calculated as the percent of trials in which the participant successfully found the goal.

3.2.2.4 Questionnaire on Spatial Representations (QSR; Pazzaglia & DeBeni, 2001).

This was used to measure self-reported preference for different solutions by asking participants to rate the extent to which 6 Likert-scale items describe their experiences and preferences during navigation and spatial learning. The items were broken down into 3 subscales based on preference for the use of landmarks, familiar paths, and global structure, with possible values range from 2-10 points for each one. The latter two subscales were used to index biases for familiar paths vs. global structure by taking a difference score, ranging from -8 (strong familiar path preference) to +8 (strong global preference), which we refer to as QSR-Style.

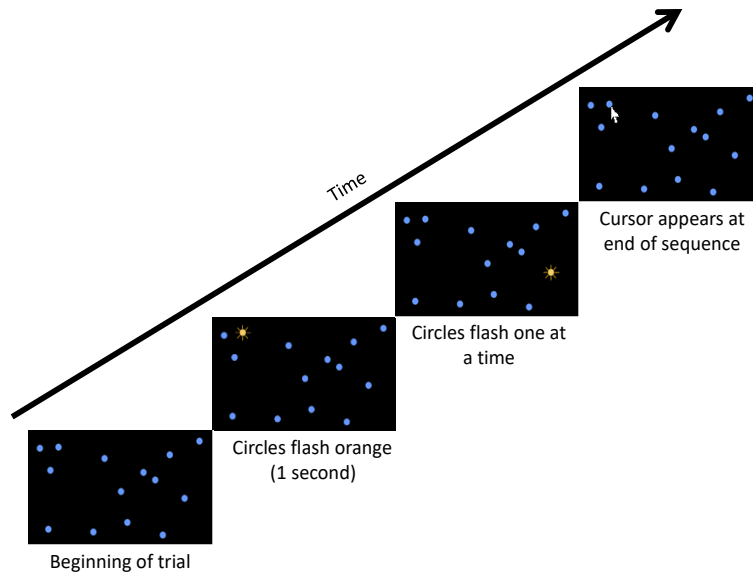
3.2.2.5 Mental Rotation Test (Vandenberg & Kuse, 1978). This was used to measure mental rotation ability, the ability to imagine and compare objects that are rotated relative to one another. On each item, participants were given a reference item and 4 samples (see Figure 7). They then decided which samples were rotated versions of the reference object. The test was separated into two parts with 10-items each, and participants were given 3 minutes to complete each section. Scores were calculated out of 40 (up to 2 points per item).

Figure 7. Example item from Mental Rotation Test.



3.2.2.6 Non-Sequential Corsi Block (Gmeindl et al., 2011). The Non-sequential Corsi Block task measures spatial working memory, an individual's ability to maintain spatial information in memory. In this task, participants were presented a set of 14 circles on a computer screen (see Figure 8). On each trial, n circles flashed orange, one at a time. Once the sequence had finished, a tone was played and participant responded by clicking with a mouse on each circle they saw flash orange. The circles could be selected in any order. The experiment started at $n = 3$ circles that flashed during a trial. After a successful trial, n was increased by 1, whereas after an unsuccessful trial n was decreased by 1 (e.g. if trial 1 was completed successfully, trial 2 would have $n = 3+1$ items). Participants completed 15 total trials. Spatial working memory span was calculated as the highest level of n a participant successfully completed, such that 18 was the highest possible span.

Figure 8. Diagram of the Non-Sequential Corsi Block task. A set of blue circles appear on the screen, there is a 1 second delay, then n circles, one at a time, flash orange for 1 second. Following this, a cursor appears on the screen and participants are instructed to click on all circles that turned orange in any order.

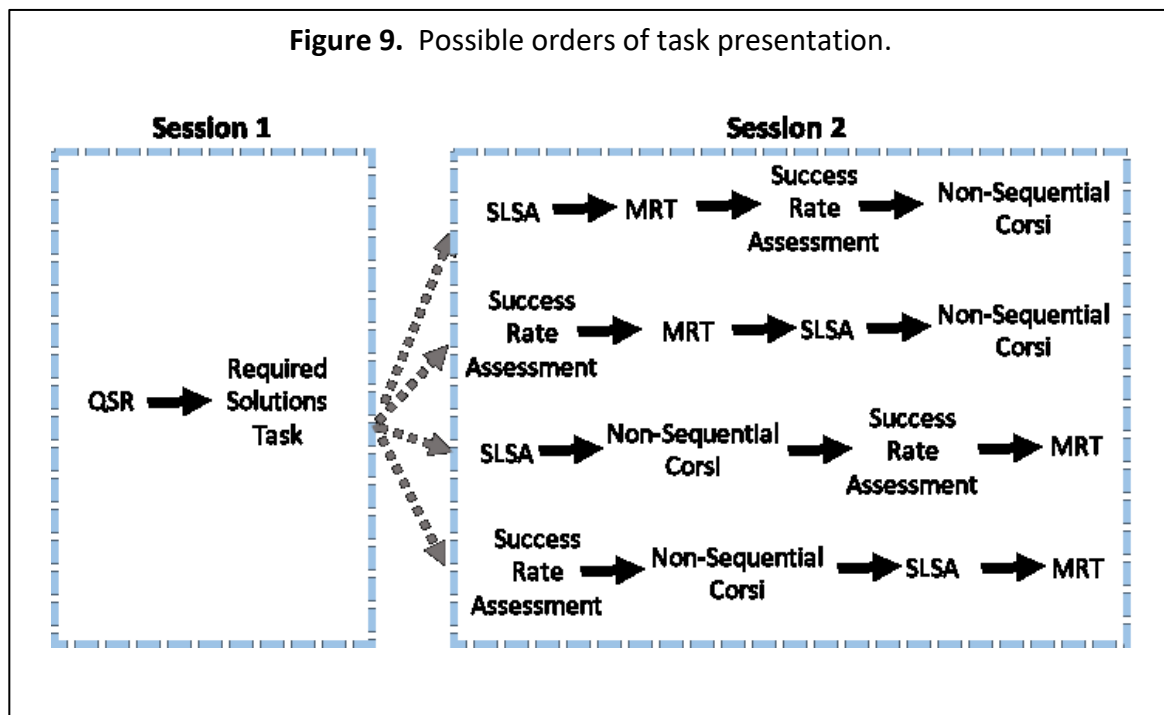


3.2.3 Timing. All of the above measures required approximately 3 hours to complete.

To reduce the likelihood of fatigue from completing so many similar tasks, the study was completed in two sessions on separate days. On each day, participants completed half of the measures (as outlined below) and were offered the opportunity to take short breaks between tasks during each session. These breaks were at most several minutes. Most participants used at least one break per session and typically either sat quietly or went to the bathroom during these breaks.

3.2.4 Task Order. As noted by previous research, there is the potential for cross-contamination among measures. The order of tasks was carefully chosen to minimize this risk based on some key considerations. The first goal was to ensure that the Questionnaire on Spatial

Representation was completed first because previous research has suggested recent experiences with navigation can sometimes influence self-report responses (Lee et al., in prep; Heth et al., 2002). As such, we opted to have this completed first by all participants to avoid any influence. A second consideration was the need to separate the three navigation tasks: Required Solutions, Success Rate Assessment, and the SLSA. This required splitting these critical tests over the two different sessions, and we opted to have the Required Solutions Task in the first session because of the length of the task and to avoid any possible influence of doing tasks that allow volitional switching. To address separation between the Success Rate Assessment and the SLSA, we use the remaining spatial skill tasks in a counterbalanced order. Figure 9 shows the four different task orders.



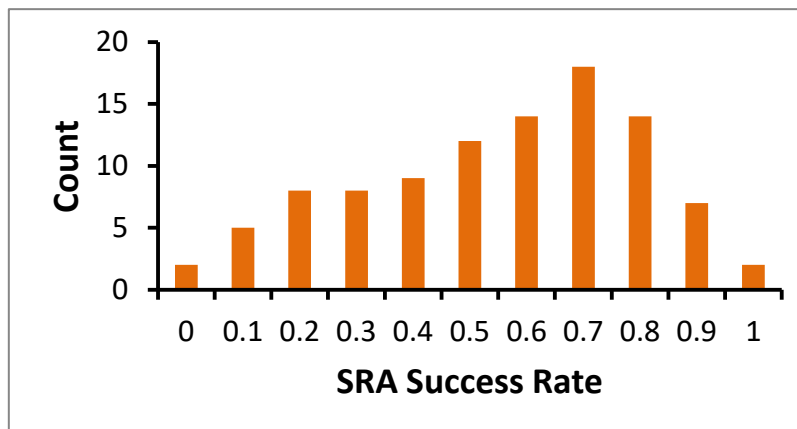
3.3 Results

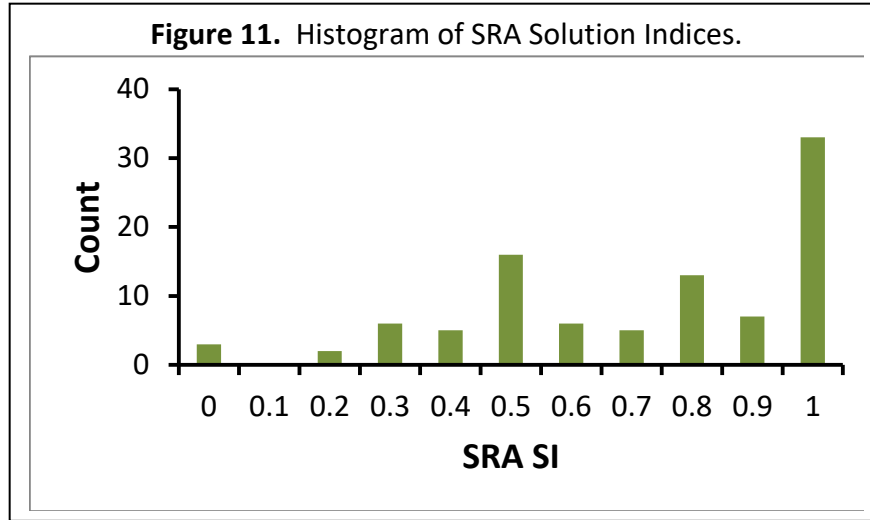
3.3.1 Characterization of Performance on New Tasks. Before proceeding to the analyses, it is important to briefly characterize how participants performed in the new measures

introduced in this experiment. Other articles, detailed above, offer more thorough descriptions of performance on the measures used in previous work.

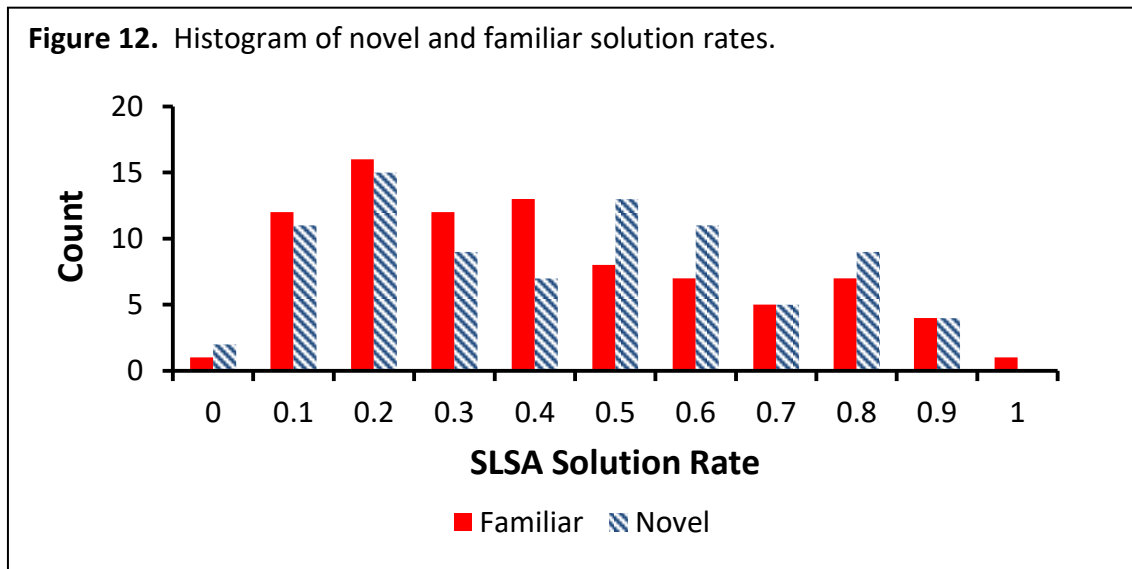
3.3.1.1 Success Rate Assessment. The Success Rate Assessment was intended to measure how successful an individual tends to be when navigating by measuring how often he/she is able to find a goal location when multiple kinds of solutions are available. This measure is, obviously, critical to an investigation of successful navigation. In order to be useful for this purpose, participants needed to fall along a wide range of points on a continuum of always successful to never successful. A trial was considered successful if the participant made it to the goal location within the allotted time limit. In this sample, mean success rate was 0.55, $SD = 0.25$. As can be seen in Figure 10 the distribution is slightly left-skewed, but critically the entire range of success rates is represented. Although this skew is not ideal, it is slight and the data fall along the entire continuum of success rates, so the measure appears to be well-suited for the purposes of this experiment.

Figure 10. Histogram of success rates on the Success Rate Assessment.





Next, we want to evaluate whether the kinds of solutions used in this task differ from the kinds of solutions used in other performance-based methodologies such as the SLSA or DSP. As a first pass at this, we examined the Solution Indices, which measure an individual's relative use of novel versus familiar solutions. This measure has been used in other performance-based navigation tasks (e.g. Chapter 2; Furman et al., 2014; Marchette et al., 2010) and thus serves as a good comparison. On the Success Rate Assessment, mean SI was 0.70, $SD = 0.29$. This was notably different from the SIs obtained in Chapter 2 for the DSP (mean = 0.45, $SD = 0.26$) and SLSA (mean = 0.51, $SD = 0.27$). To understand why the SIs from the Success Rate Assessment differ from those taken from the DSP or SLSA, we examined the histogram of SIs (Figure 11). The shape of this distribution resembles the distributions of SLSA and DSP SIs (Figure 3), except that there are far more participants with an SI of 1. This increase in novel-solution users could occur for several reasons. It could be that individuals are using a large number of novel solutions and this is increasing SIs. Conversely, it could be that individuals are using few familiar solutions this in turn increases SIs. Finally, it could be the case that the smaller number of successful trials, which are needed to determine solution use, is leading to more extreme

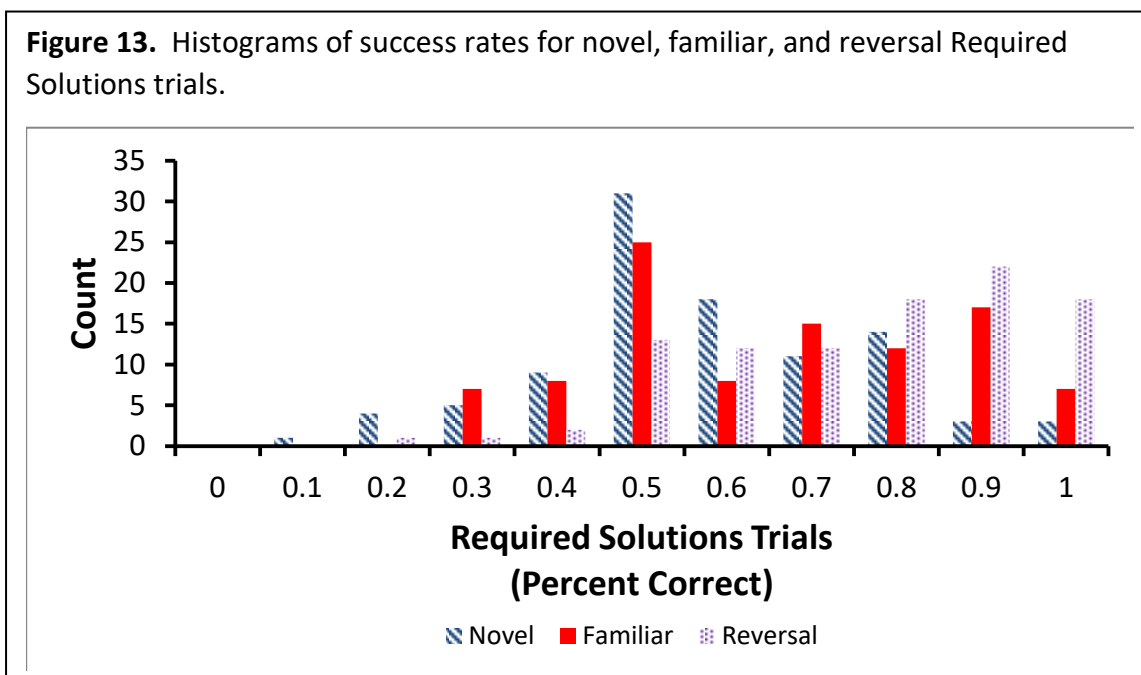


values of SI. An inspection of the distributions of familiar and novel solution rates, the percentage of successful trials on which each kind of solution was used, indicated that the distributions do not appear to be meaningfully different (Figure 12). Critically, in contrast with SI, this measure included reversal solutions in the denominator. When those were included, there were no participants who only used novel solutions, although there were many who used *almost* only novel solutions. Given that these distributions of novel and familiar solutions did not appear to differ meaningfully and that there was not an abnormally large number of individuals using exclusively novel solutions, the increase in participants with high SIs appeared to be an artifact of the lower success rates compared to the SLSA. Thus, in sum, the Success Rate Assessment satisfies all of the requirements to believe that it is accurately measuring how successful an individual is when they navigate.

3.3.1.2 Required Solutions Task. The Required Solutions Task was designed to measure an individual's capacity for each of the three solution types: novel, familiar, and reversal. As was the case for the Success Rate Assessment, for this task to be useful for the present experimental purposes it needed to capture a wide range of variability in capacities for each kind

of solution. As can be observed in Figure 13, there was a wide range of success rates for each kind of trial. This fits the requirements for the present study that individuals are differing in their capacities and representing nearly the entire range of possible capacities.

Next, we examined the correlations between each of these capacities to see how closely they align with the same correlations from a previous study using the DSP methodology (Shelton et al., in prep). In the DSP variation of this task, there was a significant correlation between familiar and reversal capacities, $r = +0.67$ (Shelton et al., in prep). In the present variation, this correlation was $r = +0.45$, which was not significantly different, $z = 1.68, p = 0.093$. In the DSP variation of this task, there was also a significant correlation between novel and reversal capacities, $r = +0.45$ (Shelton et al., in prep). In the present variation, this correlation was $r = +0.57$, which was not significantly different, $z = -0.84, p = 0.401$. Finally, in the DSP variation of this task, the correlation between familiar and novel capacities was not significant, $r = +0.22$ (Shelton et al., in prep). In the present variation, this correlation was significant, $r = +0.55$,



which was significantly different, $z = -2.04$, $p = 0.041$. Thus something about the single-trial nature of this variation of the task gave rise to more closely related measures of novel and familiar solution capacity. One possibility for this is that single-trial nature of this variation allows one to remain grounded in the environment at all times, allowing for online updating of spatial information, whereas the DSP-based variation required more offline updating.

3.3.2 Key Question and Measures. Before proceeding to the analyses, it is important to clearly lay out the key questions of the study and which measures are used to represent the different constructs. The question of interest is quite simple – *which factors contribute to individual differences in successful navigation?* But because there are many potential factors that may contribute to these differences, the variables and analyses used to answer this question are considerably more complex. There are four categories of factors that are investigated in the following section: spatial skills, navigational preferences, capacities for different solutions, and behavioral biases for different solutions. The measurement of the first three categories is fairly straightforward.

The first set of factors we expected to relate to successful navigation was spatial skills. Theoretically, this would indicate that not only are spatial skills engaged when one navigates, but that the operations used in navigation are such that additional processing power, in the form of more efficient spatial transformations, leads to better results. This would also be in favor of environmental structure learning being the same as or similar to successful navigation because the spatial skills have been shown to relate to such environmental learning. Two such skills were used here. Mental rotation, the ability to imagine objects rotating in space, was measured by scores on the Mental Rotation Test. Spatial working memory, the ability to maintain and manipulate spatial information in memory, was measured by span on the Non-Sequential Corsi

Block task. These have been shown to relate with environmental structure learning and, to the extent to which good environmental structure learning is the same as successful navigation, these skills should directly contribute to success.

The next factor we expected to relate to successful navigation was one's preferences for the kinds of solutions they use. A preference for the use of novel solutions has been related to good environmental structure learning. If we replicate this for successful navigation, it is a mark in favor of environmental structure learning being closely related to successful navigation. Furthermore, finding any kind of preference being related to success would be an indication that the process of selecting a solution when navigating is a critical part of getting to one's destination. Preference was operationalized as the relative preference for information about the global structure of the environment, which underlies the use of novel solutions, versus information about previously traversed paths, which underlies the use of familiar solutions. Preference for information about global structure and previously traversed paths were measured by self-reported subscales from the Questionnaire on Spatial Representations. The difference between these scales, termed QSR-Style, was used to measure preference for different solutions.

Another possibility we investigated was that it is not the kinds of solutions one has a bias or preference for that matters, per se, but the extent to which that person can flexibly use different kinds of solutions at different times. This was operationalized as the extent to which an individual spontaneously used a mixture of solutions on the SLSA. To obtain a measure of this, we used the formula $|\text{SLSA SI} - 0.5|$, which created a 0 – 0.5 scale where 0 represented a perfect balance between using familiar and novel solutions and 0.5 represented using only one kind of solution. Finding this to be related to success would support the importance of the solution selection process in successful navigation and indicate that being able to flexibly apply different

solutions to different situations, perhaps when the solution best corresponds to the situation, is critical to getting to one's destination.

A final possibility is that one's capacity for using specific kinds of solutions is critical to success. The capacity to use a solution was defined as how often one was successful when they are forced to use that solution to navigate. The capacity to use one specific solution is different from success when any solution is available. This would not be the case if a given individual only used one kind of solution every time they navigated, but previous research indicates that this at most very rarely the case (e.g. Chapter 2; Furman et al., 2014; Marchette et al., 2010). Instead, most individuals use a variety of different solutions when they navigate, which indicates that they must somehow be adjudicating between these. Thus, in unconstrained navigation, variance in success may be related to aspects of the selection of a solution in addition to an individual's capacity for specific solutions.

Even if the selection process isn't critical, these capacities remain separate from successful navigation and may be telling us something about what predicts success. For example, it could be that the capacity to use novel solutions is predictive of success even when an individual uses other kinds of solutions. This would indicate that learning information about the structure of the environment, which underlies novel solution use, may play a role in success with any strategy. As a measure of capacity, participants were instructed to use a specific kind of solution for trials on the Requires Solutions task. These included familiar, novel, and reversal trials. For each kind of solution, an individual's capacity was measured as the percent of trials requiring the use of that solution in which the participant found the goal location.

3.3.3 Relationships among measures. Now that we have covered the measures that were included in this experiment, we can examine the relationships among them. This was

important for several reasons. First, it allowed us to anticipate any potential collinearity among our measures, which would be an issue for using regression to understand the prioritization of these variables as predictors of success. Collinearity increases standard errors, obscuring potentially significant relationships, and decreases the stability of the beta weights in the regression equation, which leads to inaccurate estimates of the relative importance of predictors. Second, inspecting these relationships can provide hints as to any potential mediating relationships that might be revealed with the regressions. All correlations are shown in Table 8.

The two measures of spatial skills, Mental Rotation Test scores and Non-Sequential Corsi Block span, were correlated, $r = +.41$, consistent with previous research (e.g. Hegarty et al., 2006). Mental Rotation Test scores were also correlated with all aspects of the Required Solutions task, capacity for familiar solutions, $r = +.48$, novel solutions, $r = +.39$, and reversal solutions, $r = +.32$. Working memory span on the Non-Sequential Corsi Block task was positively correlated with capacity for familiar solutions, $r = +.37$ and with flexibility of solution use, the propensity to use multiple kinds of solutions in different situations when navigating, $r = +.28$. Of particular interest in this study, span on the Non-Sequential Corsi Block task was correlated with success rate on the SRA, $r = +.36$. These correlations were not strong enough to individually act as collinear variables, but they did suggest multiple relationships that could be a problem in our regression models, which we subsequently tested for. The large number of correlations between spatial skills measures and other variables indicated that the spatial skill measures were unlikely to contribute unique variance to success above the contributions of these other variables. This could be an indication that another variable is mediating the relationship between spatial skills and success. Furthermore, given the indications from previous research

Table 8. Correlations between all measures in experiment 3. * indicates significance at $p = 0.05$. ** indicated significance at a Bonferroni-corrected $p = 0.05$.

	Non-Sequential Corsi Block	QSR-Style	SLSA Familiar Rate	SLSA Novel Rate	SLSA Reversal Rate	SLSA SI	SRA Success Rate	Required Familiar Solution	Required Novel Solution	Required Reversal Solution	Flexibility of Solution Use
Mental Rotation Test	.407**	0.211*	-.038	-.028	.084	-.009	.221*	.479**	.387**	.319**	-0.102
Non-sequential Corsi Block		.026	.065	-.017	-.065	-.018	.362**	.365**	0.225*	.290*	.284**
QSR-Style			-.199*	.096	.110	.122	.057	.033	.199*	.180	-0.09
SLSA Familiar Rate				-.693**	-.290**	-.878**	.269*	.247*	.116	.043	-0.092
SLSA Novel Rate					-.488**	.873**	-.124	-.127	.004	-.029	0.01
SLSA Reversal Rate						-.095	-.159	-.129	-.149	-.018	0.098
SLSA SI							-.217*	-.189	-.096	.009	0.047
SRA Success Rate								.525**	.446**	.409**	0.093
Required Familiar Solution									.552**	.450**	-0.026
Required Novel Solution										.527**	-0.117
Required Reversal Solution											-0.141

that these spatial skills are related to environmental structure learning, the measures of capacity were prime candidates to be potential mediators.

In contrast, QSR-Style, the measure of *preference* for solutions, was not significantly correlated with anything. Thus there was no reason to be concerned about potential collinearity with this measure. But there was also no indication that navigational preferences are related to success because of the lack of correlation between these measures of preference and SRA success rate. This was particularly interesting because these preferences are related to measures of environmental structure learning, which is consistent with environmental structure learning being different from successful navigation.

Flexibility of solution use, a measure of a person's tendency to spontaneously use different kinds of solutions, was only significantly correlated with Non-Sequential Corsi Block spans, $r = +0.28$. This correlation was not strong enough to warrant concern about collinearity in a regression. It did, however, add more support to the idea that the behaviorally-measured constructs may be playing a mediating role between spatial skills and successful navigation.

All of the measures of capacity were related to one another. The capacity to use novel solutions, taken from the Required Solutions task, was correlated with the capacity to use familiar solutions, $r = +0.55$, and the capacity to use reversal solutions $r = +0.53$. The capacity to use familiar solutions was correlated with the capacity to use reversal solutions $r = +0.45$. These results replicated those from Shelton et al. (in prep), with the exception of the relationship between novel and familiar capacities. In Shelton et al. (in prep), these were only weakly correlated, $r = +0.22$.

All capacities were correlated with success rate, $r_s > 0.40$. These moderate to strong correlations indicated that the capacities for individual kinds of solutions were contributing to an individual's overall success rate. Regression analyses will be critical for disentangling the unique contributions of each because they were strongly inter-correlated. It could be the case

that one or more of these capacities was only contributing to success by virtue of shared variance with other capacities. If multiple capacity measures are uniquely contributing, regression will also be useful in understanding the prioritization of the contributions of these capacities. Furthermore, these will need to be examined for potential collinearity because of the inter-correlations.

3.3.4 Biases. The final set of factors we were interested in was biases for solution use. These behaviorally-measured biases may differ from self-reported preferences. In previous work, the only measure used in these kinds of tasks has been the relative use of novel versus familiar solutions (SI). This measure has not typically been associated with success rate. As such, we did not expect that it would be particularly impactful by itself. But more recent work has found evidence for the usage of reversal solutions, which seem to rely on having both a sense of global structure and knowledge of specific paths. However this work has not directly investigated the relationship between the bias to use reversals and one's overall success when navigating. Ideally, bias for reversals would be included in any assessment that aims to understand success.

One way to include this construct would be to include the three different measures of bias for solution use from the SLSA (novel, familiar, and reversals). This is problematic though. Each of these measures is the proportion of classifiable trials on which an individual used that kind of path. Thus, we know in advance that these are relative proportions of each other, so they are clearly not going to be independent. That is, if you know any two, you can perfectly predict the third one, so they are, by necessity, collinear. Thus there is no way for these to be meaningfully included in a regression-based analysis.

There is another possibility for including the bias for reversals. SI represents information about bias for novel and familiar solutions, but the transformation from individual proportions to a ratio makes it not perfectly collinear with bias for reversals. In fact, the correlation between SI and reversals was exceedingly weak, $r = +0.01$. Furthermore, after we removed novel and familiar solution biases from consideration, we found that none of the other potential predictor variables were significantly correlated with SI or reversal bias, indicating that they were not collinear with other predictors, $r_s < .19$. Interestingly, reversal bias was not significantly correlated with success rate, $r = -0.16$, indicating that the propensity to use reversals does not likely contribute to one's success when navigating. SLSA SI was weakly correlated with success rate, $r = -0.22$, indicating that the propensity to use familiar solutions may relate to overall success when navigating. Including both SLSA SI and reversal rate in the same model appears to be a promising way to include the bias for reversal solutions into the evaluation of successful navigation. But, before modeling successful navigation, potential gender differences in the measures needed to be addressed.

3.3.5 Gender Differences. Although the primary focus of this work was not gender differences, it remains important to examine the data for and gender differences before proceeding to the primary questions of interest. Finding gender differences in a measure may indicate different ranges or distributions of data points in that measure for each gender. This could potentially alter the relationship between these measures and success, which would lead to different predictors of success for each gender. Systematic gender differences could also artificially produce overall relationships with success. For example, if females score highly on measure A and males score poorly on measure A, then we could spuriously find measure A to be correlated with success when in fact no such relationship exists for each gender separately.

Table 9. Means and standard deviations for all measures in Experiment 3. Significant gender differences are displayed in bold.

Measure	Overall	Male	Female	Comparison
Mental Rotation Test	19.55 (8.95)	22.7 (9.2)	16.6 (7.7)	$t = 3.27, p = 0.001$
Non-Sequential Corsi Block	7.45 (2.33)	7.27 (1.78)	7.54 (2.55)	$t = 0.62, p = 0.537$
QSR-Style	-0.34 (2.46)	0.23 (2.25)	-0.87 (2.54)	$t = 2.27, p = 0.026$
SLSA Familiar Rate	0.34 (0.24)	0.35 (0.24)	0.34 (0.24)	$t = 0.12, p = 0.909$
SLSA Novel Rate	0.40 (0.26)	0.40 (0.26)	0.40 (0.26)	$t = .008, p = 0.939$
SLSA Reversal Rate	0.26 (0.19)	0.26 (0.20)	0.26 (.019)	$t = .009, p = 0.931$
SLSA SI	0.53 (0.30)	0.52 (0.31)	0.54 (0.30)	$t = 0.27, p = 0.787$
SRA Success Rate	0.55 (0.25)	0.62 (0.22)	0.49 (0.25)	$t = 2.60, p = 0.011$
Required Familiar Path	0.61 (0.20)	0.69 (0.16)	0.54 (0.21)	$t = 4.04, p < 0.001$
Required Novel Path	0.53 (0.18)	0.60 (0.17)	0.48 (0.18)	$t = 3.34, p = 0.001$
Required Reversal Path	0.71 (0.18)	0.79 (0.16)	0.65 (0.17)	$t = 4.20, p < 0.001$
Flexibility of Solution Use	0.26 (0.16)	0.26 (0.17)	0.26 (0.15)	$t = 0.08, p = 0.935$

Participants were asked to report their gender by circling either “Male” or “Female” on a demographics form prior to completing the experiment. These data were examined for any potential gender differences (Table 9). Consistent with previous research, we found that males

(mean = 22.7) performed better than females (mean = 16.6) on the Mental Rotation Test (e.g. Vandenberg & Kuse, 1976), $t = 3.27$, $p = 0.001$. Males (mean = 0.23) tended to have a stronger preference for global structure solutions relative to familiar solutions on the Questionnaire on Spatial Representation compared to females (mean = -0.87) (e.g. Pazzaglia & DeBeni, 2001), $t = 2.27$, $p = 0.026$.

With respect to our navigational tasks, males tended to have higher success rates than females. Males (mean = 0.62) had higher success rates on the Success Rate Assessment task than females (mean = 0.49), $t = 2.60$, $p = 0.011$. Males (mean = 0.69) performed better than females (mean = 0.54) on the Required Solutions familiar solution trials, $t = 4.04$, $p < 0.001$. Males (mean = 0.60) performed better than females (mean = 0.48) on the Required Solutions novel solution trials, $t = 3.34$, $p = 0.001$. Males (mean = 0.71) performed better than females (mean = 0.65) on the Required Solutions reversal solution trials, $t = 4.20$, $p < 0.001$.

As mentioned above, these gender differences could lead to spurious relationships in the full sample or to different patterns of results for each gender. These differences can be analyzed by using separate regressions for each gender or by including gender as a categorical variable in the analyses. Including gender as a categorical variable would allow us to examine the extent to which gender predicts success and to control for gender effects. Doing separate analyses would allow us to directly examine whether different sets of variables predict success for each gender. In order to understand successful navigation, it is important to understand whether the factors that make one successful are different for different genders. Thus, each of the following analyses was done for all participants and then for each gender separately. But, doing this greatly reduces the sample size, which can lead to less stable estimates. In order to hedge for this, we will also present the analyses with gender as a categorical variable.

3.3.6 Understanding Unique Contributions to Success. Based on the correlations presented above, we have an idea of some constructs that were related to success. Spatial working memory and all three measures of capacity were contributing in some way to one's overall success when navigation. A bias towards using familiar solutions was also weakly related to success. Now that we have an idea of which constructs related to success, we can take the next step of examining how these constructs contribute to success uniquely. That is, to what extent do these measures explain variance in success rates above and beyond the explanatory power of all other measures?

Based on the discussion of measures of bias, we used multiple sets of simultaneous regressions to understand what the best way of capturing bias is in these analyses. Before proceeding to the actual regression though, we first examined whether these predictor variables were collinear with one another. Collinearity increases standard errors, obscuring potentially significant relationships, and increases the instability of the beta weights in the regression equation, which leads to inaccurate estimates of the relative importance of predictors. Put simply, when predictor variables are collinear, the model created through regression is still good at predicting, but the contributions of individual variables become less reliable. Given that the purpose of this experiment is to understand how individual predictors are contributing to success, we needed to use a model that does not exhibit significant collinearity.

3.3.6.1 SI. The first method of operationalizing bias we investigated was to use only SLSA SI, which measures the relative bias for novel versus familiar solutions. To inspect the predictors for collinearity, the measures of spatial skills, preference, capacity, flexibility of solution use, and SI were entered into a simultaneous regression predicting SRA success rate. Variance inflation factors (VIFs) for each predictor were inspected for potential collinearity.

VIF is the reciprocal of tolerance and represents the amount that the variance in a coefficient is inflated relative to what would be expected if there were no multicollinearity present. A variety of recommendations exist for the highest level of VIF to tolerate in a dataset, from 10 (e.g. Neter, Wasserman, & Kutner, 1989) to 4 (e.g. Rogerson, 2001). To preview that data, no VIFs > 3 were found, indicating no significant collinearity at even the strictest recommended criterion. No significant collinearity was found in this regression, VIFs < 2.2. Now that we know there was

Table 10. Simultaneous regressions predicting SRA success rate.

	SI		SI + Reversal		SI + Reversal + Gender	
	Standardized β	sr^2	Standardized β	sr^2	Standardized β	sr^2
Mental Rotation Test	-0.02	0.00	0.00	0.00	-0.02	0.00
Non-Sequential Corsi Block	0.16	0.02	0.16	0.02	0.19	0.02
QSR-Style	0.07	0.01	0.09	0.01	0.07	0.00
SLSA SI	-0.24	0.05	-0.26	0.06	-0.27	0.06
Familiar Capacity	0.25	0.03	0.23	0.02	0.21	0.02
Novel Capacity	0.28	0.04	0.25	0.03	0.24	0.03
Reversal Capacity	0.15	0.01	0.18	0.02	0.14	0.01
Flexibility	0.13	0.01	0.14	0.02	0.13	0.01
Reversal Rate	-	-	-0.16	0.02	-0.16	0.02
Gender	-	-	-	-	0.10	0.01

no collinearity, we can proceed to examine the regression (Table 10) to see what can be learned about these predictors' unique contributions to success.

This simultaneous regression resulted in a significant model, $R^2 = 0.494$, $F(8, 90) = 7.196$, $p < 0.001$. Although it was encouraging that this model accounted for a large portion of the variance in success rate, for our present purposes the more important aspect was to understand how the individual predictors are relating to success rates. First, we observed that the relationships among predictors and success in the regression were in the same direction as the simple correlations were. This revealed that there were no suppressor variables. Next, we examined the standardized β values in order to understand the extent to which the increase in a predictor variable changes the predicted value of success. This gave us an understanding of which variables were providing the greatest contributions to predicting success rate. Three such β s stood out: novel solutions capacity, $\beta = 0.28$, $t = 2.19$, $p = 0.031$, familiar solutions capacity, $\beta = 0.25$, $t = -2.42$, $p = 0.028$, and SLSA SI, $\beta = -0.24$, $t = 1.88$, $p = 0.063$, which was only marginally significant. These three factors appeared to be offering the stronger independent contributions to predicting success.

Also of interest were two predictors, Non-Sequential Corsi Block span and reversal solution capacity, which were significantly positively correlated with success rate, $r_s > +0.40$, but did not have strong β s for predicting success, $\beta_s < 0.16$. This suggested that their contributions to success rates based on the simple correlations were due at least in part to their shared variance with other, stronger predictors. This was not surprising. As noted earlier, spatial working memory was correlated with many measures in this study and it would not be surprising if performance-based measures of navigation were in some way recruiting working memory. Thus spatial working memory may be acting as a mediator variable between the performance-based measures and success. Reversal solution capacity, on the other hand, has been hypothesized to be a combination of novel and familiar solution capacity. This is consistent with

the pattern we observed here – if novel and familiar solutions are making unique contributions to success, then there is little unique contribution left for reversal solution capacity to make. These issues will be more thoroughly examined in a later section.

Returning to the examination of individual contributions, we next turned our attention to sr^2 values. These values represent the percent of the variance accounted for by a given variable after accounting for all of the other variables in the current model (i.e., as if it were the last variable added). Whereas β s represent the weight given to a variable in the predicted success, sr^2 represents the importance of a variable in accounting for actual success (comparing predicted and observed). Once again, three variables stood out as contributing the most to the variance in success rates. In order, they were SLSA SI, $sr^2 = 0.01$, novel solution capacity, $sr^2 < 0.01$, and familiar solution capacity, $sr^2 < 0.01$. Interestingly, the order of these was different for sr^2 than for the β s. Given that the purpose of this study was to understand the factors contributing to success rather than create an equation for explicitly predicting success, the ordering of the sr^2 values is more relevant.

In summary, this analysis suggested three factors that are important for successful navigation: the ability to use novel solutions, the ability to use familiar solutions, and a bias to use familiar solutions. There was also preliminary evidence that spatial working memory may be important for these abilities and bias. The next step in understanding successful navigation was to add in our other measure of bias, reversal rate, and see how this affected the observed relationships.

3.3.6.2 Reversals. Next, we wanted to see what accounting for the bias to use reversal solutions would contribute to the explanation of success. To do this, we ran the same

simultaneous regression as before but also included SLSA reversal rate as a predictor. As a reminder, SI was used to represent both novel and familiar paths so that it would remain independent of the reversal rate. No new collinearity was introduced with the addition of reversals, $VIFs < 2.2$.

This simultaneous regression (Table 10) resulted in a significant model, $R^2 = 0.517$, $F(9, 89) = 6.901$, $p < 0.001$. Upon inspecting the standardized β values, we found many of the same patterns as in the first regression. SLSA SI, $\beta = -0.26$, $t(90) = -2.63$, $p = 0.010$, novel solution capacity, $\beta = 0.25$, $t(90) = 1.97$, $p = 0.052$, and familiar solution capacity, $\beta = 0.23$, $t(90) = 1.68$, $p = 0.096$, stood out as contributing the most to the prediction of success. Familiar solution capacity was no longer a marginally significant predictor, though. Thus once the bias to use reversal routes has been taken into account we found that novel solution capacity and the bias to use relatively more familiar solutions than novel solutions were still contributing to the prediction of success. The bias to use reversal solutions did not appear to be significant in predicting success, $\beta = -0.16$, $t(90) = -1.67$, $p = 0.098$, indicating that an individual's bias to use reversal solutions does not uniquely add to our understanding of whether they will typically be successful when they navigate.

As was found in the previous regression, there were two predictors, Non-Sequential Corsi Block span and reversal solution capacity, which were significantly positively correlated with success rate, $r_s > +0.40$, but do not show strong β s for predicting success, $\beta_s < 0.16$. This was consistent with the pattern we observed in the previous analysis – if novel and familiar solutions are making unique contributions to success, then there is little unique contribution left for reversal solution capacity to make. These issues will be thoroughly examined in a later section.

Next we turned our attention to sr^2 values to understand how well each predictor accounts for the variance in success. Two variables stood out as contributing the most to the variance in success rates. In order, they were SLSA SI, $sr^2 < 0.01$, and novel solution capacity, $sr^2 < 0.01$. This followed the pattern found for β values and is consistent with a bias for familiar solutions and a capacity for novel solutions being the best indicators of success when navigating.

In summary, when the bias to use reversal solutions was accounted for, these analyses suggested two factors that were important for successful navigation: the ability to use novel solutions and the bias to use familiar solutions relative to novel ones. The ability to use familiar paths fell outside of significance here, possibly because the bias to use reversals shares variance with this ability. There was also preliminary evidence that spatial working memory may be important for these abilities and bias. The next step in understanding successful navigation was account for gender in the regression model to understand if this alters the pattern of results or if gender itself offers unique contributions to success.

3.3.7 Gender Differences. Next, we wanted to understand how the observed gender differences in several of the measures contributed to successful navigation. One such notable difference was that males were overall more successful than females. But how robust is this? Does gender contribute more to one's success than other factors such as capacities or biases? In order to investigate the contributions of gender to success, we ran a simultaneous regression using the same predictors above but added gender as a categorical variable.

Once again, no collinearities were found, VIFs < 2.3 . This simultaneous regression (Table 10) resulted in a significant model, $R^2 = 0.522$, $F(10, 89) = 6.229$, $p < 0.001$. This model did not account for more variance in success rate than the previous model, $F(10,89) = 0.602$, $p =$

0.808, suggesting that adding gender did not improve the model. But, based on the gender differences observed above, there remains the possibility that gender differences in other variables are significant for predicting success. This was explored by examining the contributions of each predictor.

Upon inspecting the standardized β values, we found many of the same patterns as in the previous regressions. SLSA SI, $\beta = -0.27$, novel solution capacity, $\beta = 0.24$, and familiar solution capacity, $\beta = 0.21$ stood out as contributing the most to the prediction of success. Supporting this, SLSA SI, $t(89) = -2.66$, $p = 0.010$ was a significant predictor of success. In this model, novel solution capacity was only marginally significant, $t(89) = 1.850$, $p = 0.068$. This indicates that gender shares some predictive power with novel solution capacity and may mean that novel solution capacity is more predictive for one gender than the other. Similarly, familiar solution capacity was not a significant predictor in this model, $t(89) = 1.520$, $p = 0.098$. This pattern suggested that the kinds of capacity that contribute to success may differ between genders. This was explored in the next section. Finally, no evidence was found to support gender providing a unique contribution to predicting success, $\beta = 0.10$, $t(89) = 0.776$, $p = 0.441$. Thus, if gender is critical to how successful one is when navigating, it is because different factors predict success for each gender.

As was found in the previous regression, there were two predictors, Non-Sequential Corsi Block span and reversal solution capacity, which were significantly positively correlated with success rate, $r_s > +0.40$, but did not show strong β s for predicting success, $\beta_s < 0.20$. This was consistent with the pattern we observed in the previous analysis – if the performance-based measures are making unique contributions to success, then there is little unique contribution left

for reversal solution capacity to make. These issues will be thoroughly examined in a later section.

Next we turned our attention to sr^2 values to understand how well each predictor accounted for the variance in success. Only one variable stood out as contributing the most to the variance in success rates when the effects of gender were controlled for, SLSA SI, $sr^2 < 0.01$. This followed the pattern found for β values. It supports the possibility noted above that the ability to use familiar and novel solutions may account for success in only one gender rather than both. Also supporting the conclusions drawn from inspecting the beta weights, gender added very little to uniquely explaining the variance in success rates, $sr^2 < 0.01$.

In summary, when gender was accounted for, these analyses suggested that a bias for using familiar solutions relative to novel ones was the best predictor of success. In contrast to previous models, we found that the capacities to use familiar and novel solutions were not as predictive of success. This could be explained as these capacities predicting success for one gender, but not the other. The following two sections investigated this possibility.

3.3.7.1 Males. We began this investigation by looking at the predictors of success for males. This was done by running the same regression as in the Reversals section but only including male participants (Table 11). Again, no collinearities were observed, VIFs < 2.9 , and the simultaneous regression resulted in a significant model, $R^2 = 0.641$, $F(9, 38) = 2.377$, $p = 0.032$.

When we compared the model to simple correlations, the results were notably different for mental rotation ability, $\beta = -0.14$, QSR-Style, $\beta = -0.18$, familiar solution capacity, $\beta = -.18$, and flexibility of solution use, $\beta = -0.11$. Although none of these were significant predictors of

success, $t_s < 0.73$, $p_s > 0.470$, the direction change was nonetheless of interest. In particular, it is important to note that familiar solution capacity was not predictive of success in males, consistent with that capacity being important for predicting success in females rather than males.

One variable was particularly useful for the prediction of success - novel solution capacity, $\beta = 0.70$, $t = 2.471$, $p = 0.018$. SLSA SI was the next most important variable for predicting success in males, $\beta = -0.25$, but this was not significant, $t = -1.356$, $p = 0.183$. This pattern of results supports the hypothesis that different solution capacities are related to success for males and females. Specifically, it appears to be the case that for males, the ability to use novel solutions provides the most unique predictive value of any factors. The lack of significance of SLSA SI may indicate that the bias for using familiar solutions may be relatively more important for predicting success in females than males.

Once again, novel solution capacity accounted for the largest portion of the variance, $sr^2 = 0.18$, followed by SLSA SI, $sr^2 = 0.05$, but as mentioned above SLSA SI was not significant. Thus, in terms of both predicting and accounting for the variance in success, the capacity to use novel solutions was the primary contributor for male navigational success.

In summary, these results from analyses supported the hypothesis that success is predicted by different factors for each gender. More specifically, they indicated that the most important factor contribution to navigational success in males is the ability to use novel solutions. This is particularly interesting because we found no evidence for males actually using more novel solutions than females. It is not the case, then, that novel solution capacity predicts success in males because they use more novel solutions.

Table 11. Simultaneous regressions predicting SRA success rate by gender in Experiment 3.

	Male		Female	
	SI + Reversal		SI + Reversal	
	Standardized β	sr^2	Standardized β	sr^2
Mental Rotation Test	-0.14	0.01	0.09	0.01
Non-Sequential Corsi Block	0.12	0.01	0.16	0.01
QSR-Style	-0.18	0.02	0.03	< 0.01
SLSA SI	-0.25	0.05	-0.29	0.07
Familiar Capacity	-0.18	0.01	0.30	0.04
Novel Capacity	0.70	0.18	0.11	0.01
Reversal Capacity	0.17	0.01	0.11	0.01
Flexibility	-0.11	0.01	0.26	0.06
Reversal Rate	0.00	0.00	-0.17	0.03

3.3.7.2 Females. The male data provided partial support for the hypothesis that male and female models might differ, so the next step was to run the same regression as in the Reversals section but only including female participants (Table 11). No collinearities were observed, VIFs < 2.0, and the simultaneous regression resulted in a significant model, $R^2 = 0.518$, $F(9, 43) = 4.296$, $p < 0.001$.

First, we observed that the relationships among predictors and success in the regression were in the same direction as the simple correlations. For the predictors, familiar solution

capacity had the numerically highest beta, $\beta = 0.30$, although this only marginally significant, $t = 1.841$, $p = 0.073$. The next two best predictors, SLSA SI, $\beta = -0.29$, and flexibility of solution use, $\beta = 0.26$, were statistically significant, $t = -2.287$, $p = 0.027$, and $t = 2.089$, $p = 0.043$, respectively. This was strikingly different from the pattern of results for males. For females, it appeared that the best unique predictors of success were the kinds of solutions they use rather than how good they are at a particular one. But, we know that there are several variables that share variance with familiar solution capacity, so although it may not be a strong *unique* predictor of success, it could still be a good predictor of success in females. This will be analyzed in a later section.

As in the combined male/female model, SLSA SI, $sr^2 = 0.07$, flexibility of solution use, $sr^2 = 0.06$, and familiar solution capacity, $sr^2 = 0.04$ accounted for the most variance. Although these were in a different order than suggested by examining the beta weights, the sr^2 values were similar enough to not warrant considering any of these as accounting for much more of the variance than any other.

In summary, these analyses supported the hypothesis that the factors contributing to success are different for males and females. For females, a bias towards using relatively more familiar solutions than novel solutions and the bias towards using a mixture of solutions best explain and predict success. This may seem contradictory at first glance. It seems odd that a bias for a specific solution and a bias for using a variety of solutions both predict success. The most likely explanation is that the best female navigators use a variety of solutions, but lean slightly more towards using familiar solutions. The next step in understanding successful navigation was to clarify the contributions spatial skills. Then all of this can be put together to better understand the prioritization of the different factors in predicting success.

3.3.8 Role of Spatial Skills. The results described above were consistent with measures of capacity playing a mediating role between spatial skills and success. To provide evidence for an indirect contribution of spatial skills, we can test for mediating variables. Finding this would indicate that spatial skills do play an important role in one's navigational success, but not a direct one. Rather it would be the case that spatial skills are directly contributing to one's ability to use specific solutions and these abilities are in turn contributing to success. This also opens the possibility that different solution capacities may be dependent on different spatial skills or even not dependent at all. The first requirement for determining a mediating variable is that the criterion variable, the predicted variable, and the mediating variable are all inter-correlated. As described above (also see Table 8), this was the case for both spatial skills, all three capacities, and success, indicating that a mediating variable is a possibility. The second requirement is to demonstrate that the indirect effect of the criterion variable through the mediating variable to the predicted variable is significantly different from zero.

Bootstrapping was chosen over other methods for this purpose because it does not assume the data are normally distributed and this method provides stable estimates for the sample size available in this study (MacKinnon, Warsi, & Dwyer, 1995). Bootstrapping is a nonparametric resampling procedure in which many samples are taken from the original data and the indirect effect of the mediator on the dependent variable is calculated for each sample. These are combined into a sampling distribution of the indirect effect of the mediator that can be used to construct a confidence interval to determine whether the indirect effect is significantly different from 0. In the present study, we used a bootstrapping procedure to compute the indirect effect for each of 5,000 samples of $n = 70$ subjects (with replacement) and constructed a 95% confidence interval for the indirect effect.

3.3.8.1 Mental Rotation. We first ran the bootstrapping procedures for mental rotation (Table 12). For novel solution capacity, the bootstrapped unstandardized indirect effect was 0.005, and the 95% confidence interval ranged from 0.002 to 0.009. For familiar solution capacity, the bootstrapped unstandardized indirect effect was 0.007, and the 95% confidence interval ranged from 0.004 to 0.011. For reversal solution capacity, the bootstrapped unstandardized indirect effect was 0.003, and the 95% confidence interval ranged from 0.001 to 0.006. Thus we concluded that the contribution of mental rotation abilities is mediated by the capacities for individual solutions, although the effect of this mediation is weak. Furthermore, in conjunction with the previous analyses, this indicated that mental rotation ability does not directly affect navigation ability beyond its effect on one's ability to use a specific solution.

3.3.8.2 Spatial Working Memory. Following the same technique as above, we examined potential mediators of spatial working memory (Table 12). For novel solution capacity, the bootstrapped unstandardized indirect effect was 0.012, and the 95% confidence interval ranged

Table 12. Unstandardized indirect effects of capacity measures mediating the influence of spatial skills on success.

Mental Rotation Test			
	Effect	Lower Bound	Upper Bound
Novel Solution Capacity	0.005	0.002	0.009
Familiar Solution Capacity	0.007	0.004	0.011
Reversal Solution Capacity	0.003	0.001	0.006
Non-Sequential Corsi Block			
	Effect	Lower Bound	Upper Bound
Novel Solution Capacity	0.012	-0.001	0.026
Familiar Solution Capacity	0.021	0.008	0.040
Reversal Solution Capacity	0.012	0.003	0.028

from -0.001 to 0.026. For familiar solution capacity, the bootstrapped unstandardized indirect effect was 0.021, and the 95% confidence interval ranged from 0.008 to 0.040. For reversal solution capacity, the bootstrapped unstandardized indirect effect was 0.012, and the 95% confidence interval ranged from 0.003 to 0.028. Thus we can conclude that the contribution of spatial working memory span was mediated by the capacities for familiar and reversal solutions, but not novel solutions. This was an indication that spatial working memory is critically engaged when manipulating information about a learned path, but not as critical when using information about the structure of the environment to determine a novel path. This may occur because individuals are using mental rotation abilities to interrogate their representation of the environment when engaging a novel solution, as opposed to calling to mind a number of navigation events when engaging a familiar or reversal solutions.

3.3.9 Understanding Prioritization of Predictors. By this point, we have gained a much better understanding of what predicts successful navigation. The above analyses demonstrated that the capacity for novel solutions and the bias for familiar solutions relative to novel solutions were the best overall predictors of success, with the capacity for familiar solutions falling just short of significance. This pattern was different for each gender though. For males, the capacity for using novel solutions was critical, accounting for 18% of the variance in variance in success rates. For females, the bias to use novel solutions and the bias to use a mixture of solutions were the most critical factors, with the capacity to use familiar solutions playing a marginally significant role.

To this point, we have an understanding of the contributors to success, but our understanding of the prioritization of these contributors needs to be clarified. The measures used to understand prioritization have focused on the unique contribution of a variable when all other

variables are held constant. These have yielded little information about which factors may be relatively more important than others because all of the significant predictors contributed similarly to the prediction of success and uniquely accounted for similar portions of the variance. Another way to think about this prioritization is to use forward regression to select a set of variables one at a time based on the contributions each variable adds to accounting for the variance in success and then examining the individual contributions of this reduced set of variables. This was only done separately for males and females rather than as an overall group because the gender difference analyses above indicated that there are different predictors for each gender and thus the results from an overall analysis could be an artifact of this.

3.3.9.1 Males. We first ran a forward regression for males using all of the predictors from the previous sections to predict SRA success rate. The criterion for inclusion to the regression was that the probability that the regression coefficient was different from 0 was < 0.05 . For males, this resulted in a one-step model that was significant, $R^2 = 0.459$, $F(1,46) = 16.944$, $p = 0.001$ (Table 13). The sole predictor in this model was novel solution capacity, $\beta = 0.677$, $t = 4.116$, $p = 0.001$. Not surprisingly, this was the same model as was predicted by examining the simultaneous regression. This supports the hypothesis that for males, the ability to understand and use novel paths in an environment is the most critical component to

Table 13. Stepwise regressions predicting SRA success rate separately for each gender.

Males			Females			
			Step 1		Step 2	
	Standardized β	sr^2	Standardized β	sr^2	Standardized β	sr^2
Novel Capacity	0.68	0.46				
Familiar Capacity			0.59	0.34	0.49	0.21
SLSA SI					-0.27	0.06

navigational success.

3.3.9.2 Females. Next we were interested in better understanding the prioritization of variables in predicting successful navigation in females. This was accomplished by using the same analyses as for males. This resulted in a two-step model $R^2 = 0.407$, $F(2,50) = 17.781$, $p < 0.001$ (Table 13). In the final step, familiar solution capacity was the best predictor of female success, $\beta = 0.49$, $t(50) = 3.873$, $p < 0.001$, $sr^2 = 0.21$. The second best predictor was SLSA SI, $\beta = -0.27$, $t(50) = -2.157$, $p < 0.036$, $sr^2 = 0.06$. These results help to clarify the results from the simultaneous regressions. Specifically, they indicate that familiar solution capacity is the best individual predictor of female success, but that this capacity also shares a lot variance with other variables, which caused it to fall just below significance in the simultaneous regression. Thus, for females a combination of being good at and using familiar solutions seems to be important for success and the ability to use familiar solutions is the best predictor of success.

3.3.10 Summary. In summary, these analyses indicated several critical things about what makes some individuals more successful than others when navigating. First, spatial skills were important for successful navigation, but their contribution was dependent on the capacities for specific solutions, indicating that different kinds of solutions utilize different spatial skills. Gender differences were observed in the factors that predict successful navigation. For males, the ability to use novel solutions was paramount to success. For females, the ability to use familiar solutions, the bias to use familiar solutions, and the bias to use a variety of solutions all contributed to success and were important in that order. In this paradigm, using novel solutions was the closest approximation to traditional measures of good environmental learning and therefore these findings are not consistent with good environmental structure learning being the same as successful navigation, particularly for females.

Chapter 4: General Discussion

Individuals differ in terms of how they navigate, the kinds of information they prefer or are biased to use when navigating, and how often they reach their goal location. For decades, we have thought about this work primarily in terms of one being good at learning the spatial structure of an environment and then being able to use that knowledge in an explicit fashion. Although there is a logical case that this knowledge could allow for one to be more successful when navigating, this does not necessarily have to be true and there is no previous empirical support to reduce successful navigation to a strong, explicit understanding of relationships between locations in an environment.

This project attempted to shift the dialog from one's knowledge of the structure of an environment predicting one's navigation to successful navigation as defined by the very practical notion of "getting there". To address this, there were two key steps. The first was to establish an appropriate set of tasks to measure success and the factors that might contribute to it. The second was to use these tasks to understand both the extent to which previous notions of good environmental learning are related to successful navigation and the factors that contribute to one's successful navigation. The results from these analyses yielded several theoretically interesting points about how humans navigate, as articulated below.

4.1 Spatial Learning Styles Assessment

Although performance-based measures of navigation have been developed previously, these methods remain time intensive and relatively inflexible in terms of the possible manipulations that can be performed because they require massed encoding of one large environment prior to test. This poses a barrier to researchers who wish to supplement or replace

self-report measures with performance-based ones. The SLSA fills this void by providing a performance-based measure of how individuals learn and navigate through an environment that is flexible and scalable.

The results of Experiments 1 and 2 provided the basis for using the SLSA as a valid and reliable measure of navigational style. First and foremost, its measures of success and SI were related to those of the DSP, indicating that they are capturing some of the same variance. The two measures also, by and large, had the same relationships with self-report and spatial skills measures. The exception to this was with mental rotation ability, which likely indicates that mental rotation ability is most critically engaged in the early moments of spatial learning. Finally, using Monte Carlo simulations, we have an indication that the results from the measures from the SLSA are relatively stable and can be obtained using as few as 6 trials.

This methodology is scalable, which allows the researcher the flexibility to use fewer trials than other similar tasks, and makes the SLSA easy to include as a part of a large battery of tests. It also allows for the use of a variety of environments, which helps to reduce the possibility of a particular environmental feature or layout biasing results. This also prevents the participant from overlearning the environment by the end of the experiment, which could also bias results. These features make the SLSA ideal for investigating questions in spatial cognition that other methodologies cannot. Of primary interest in the present study, these features make for an ideal measure of success and bias for solutions when navigating, allowing for a comprehensive investigation of the contributors to successful navigation.

4.2 Are self-reports measuring the same constructs as behavioral measures?

The past dependence on self-report techniques to understand navigational performance has been a potential limiting factor on our understanding of this critical question of successful navigation. These methods can be invaluable in some situations, but they come with strong

assumptions about the nature of the construct being investigated. Self-report measures require one to have some metacognitive knowledge of the processes being investigated and are inherently recollective and can therefore be biased. Moreover, knowing what one prefers is not the same as knowing what one can or will do.

In the present study, self-reported sense of direction was not significantly correlated with success on performance-based tasks. Likewise, self-reported preference for environmental information was not significantly related to the way participants selected their solutions. Together, these suggest a disconnection between self-report and actual navigational behavior. One previous study using the DSP found a strong correlation between self-reported preference for environmental information and bias for engaging specific solutions (Furman et al., 2014). However, this discrepancy only further serves as evidence that these self-report measures are likely telling an incomplete story about how individuals navigate. Self-reports may only reflect behavior in some individuals or they may only reflect behavior in certain environments or situations. The current results highlight the need for careful examination of the assumptions used when investigating navigation and spatial learning. As such, performance-based measures are a critical tool for these investigations.

4.3 Do spatial skills affect success?

Previous research has demonstrated that individuals with better spatial skills tend to perform better at measures of explicit environmental knowledge such as distance estimations, direction estimations, or drawing maps of the environment (Allen et al., 1996; Hegarty et al., 2004). Given this, it is entirely possible that these spatial skills have an effect on how successfully one navigates. We investigated this using two such skills, mental rotation and

spatial working memory, which have been thoroughly investigated and previously related to how well individuals learned the structure of environments.

An interesting pattern emerged with respect to spatial skills. Neither mental rotation ability nor spatial working memory directly predicted successful navigation. But the relationship between spatial skills and successful navigation was mediated by one's capacity for different solutions. The influence of mental rotation ability on successful navigation was mediated by all three kinds of solutions, indicating that the better one is at mentally rotating objects, the better they will be with any kind of solution. This in turn supports their navigational abilities. Spatial working memory's influence on success, on the other hand, was mediated by familiar and reversal solution capacities but not novel solution capacities. This is consistent with the idea that executing a familiar solution involves executing a series of remembered navigational events and that planning for this requires working memory. Similarly, it is consistent with reversal solutions being spatial manipulations of familiar solutions. In sum, these results indicate that spatial skills are important to one's success when navigating because they are used to support the different kinds of strategies one uses when navigating.

4.4 Do aspects of solution selection affect success?

By shifting from questions of what or how much one learns about the environment around them to questions about how successful one is in their goal of moving from one location to another, we open the possibility that the manner in which one selects solutions affects their eventual success or failure. This might happen because one kind of solution is simply better than others or because using a mixture of solutions leads to one being able to more flexibly tailor their solution to the present situation. Here we tested three possibilities for how solution selection may affect success when navigating.

First, it could be the case that one's preference for a kind of solution predicts how successful they are. Previous research has demonstrated that individuals with stronger preferences for information about the structure of the environment, which underlies the ability to use novel solutions, tend to perform better on measures of explicit spatial knowledge of an environment (Pazzaglia & DeBeni, 2001). This hypothesis was not supported by the data for successful navigation, indicating that subjective preference for solutions may be indicative of *what* one learns about an environment, but it is not indicative of how successful one is at navigating.

The second possibility was that one's behavioral bias for a specific kind of solution, rather than their subjective preference, is indicative of success. This would follow the same logic as the preference hypothesis. But, given that self-report measures of preference do not necessarily correspond to behavioral measures of bias, it is possible that our tendency to use a kind of solution is important to our success, but we don't have a good metacognitive understanding of what those tendencies are. This hypothesis was supported by the data, but in a different direction than previous theories predicted. We found that a preference for using familiar solutions predicted overall success and that it was predictive for females but not for males. This is particularly interesting because the measures of capacity for these solutions did not indicate that females were relatively better at familiar solutions than other kinds of solutions. In previous work, females were found to endorse using more familiar solutions than novel, orientation-based solutions (Lawton, 1996). These results take those a step further by saying that, not only might females prefer these solutions but that if they do, it is for good reason – using those leads to more success.

The third possibility is that, rather than one kind of solution being superior to the others, what is most important is being able to use different solutions at will. Being able to use different kinds of solutions at different times or in different situations might allow an individual to select a solution that works best with the environment they are in, the task they are performing, and their internal representation of the environment. This was weakly supported by the data, but only for females. For females, having a balance of solutions was predictive of success when navigating.

For males, we found no evidence that the way they select solutions is related to success when navigating. For females though, the selection process was the best predictor of success. These results indicate that the best female navigators will tend to use a mixture of solutions, but that this will be slightly biased towards familiar solutions.

4.5 Does capacity for specific solutions affect success?

As discussed earlier, in most real-world situations that require navigation, there is more than one way a person can go and still make it to their destination. We have already discussed one critical aspect of this as it related to successful navigation – selecting an appropriate solution. But there might be more contributors to success than just which solution you use. How well one uses different kinds of solutions may also influence one's overall success. For example, if someone were perfectly able to select an ideal solution every time they navigated, but he had little to no aptitude for executing some of those solutions, it is very unlikely that individual would be successful every time. In line with previous theories that learning the global structure of an environment is critical to navigating well, it could also be the case that one's capacity for solutions which require such knowledge is a particularly good predictor of success. This would

lend support to the hypothesis that being good at learning the structure of the environment is the same as being successful when navigating.

In the present study, we found that the capacity to use novel solutions, which require information about the structure of the environment, predicted successful navigation. But, it is not as straightforward as novel solutions being the best way to be successful, as has been previously posited. Critically, there were gender differences in how these capacities related to success. Novel solution capacity predicted success for males, whereas familiar solution capacity predicted success for females.

Thus it is the case that the capacity for using a solution is important to be able to navigate successfully and that the critical capacity varies with gender. It is important to note that males and females did not differ in their tendency to spontaneously use familiar or novel solutions, but did differ in their preference for such solutions, such that females had stronger preferences for familiar solutions and males had stronger preferences towards novel solutions. Thus, it does not appear to be the case that each gender tends to use one kind of solution more often and this leads to the capacity for that solution being critical.

Males were overall better at the capacity for all three kinds of solutions, but the relative ability for using each solution was the same for both genders. That is, the two genders showed similar patterns of capacity for the different solutions, but females' capacities were uniformly lower. Thus it is also not the case that each gender has a different "best" kind of solution and that is driving this effect. In fact, both genders were best at reversal solutions and yet the capacity for reversals did not significantly contribute to overall success.

This difference could be cultural in nature. Previous studies have found that males typically have more opportunities to use spatial abilities as children and that these experiences are important to developing strong spatial abilities in adulthood (e.g. Baenninger & Newcombe, 1995; Terlecki & Newcombe, 2005; Terlecki, Newcombe, & Little, 2008). Using inventories of childhood activities, these studies have found that male children are given more free reign to explore their surroundings as children relative to females. These studies also found that male children tended to engage in more activities that require spatial thinking and navigation. For example, males were proportionally more involved in sports, which require spatial processing. Baenninger & Newcombe (1995) noted that many stereotypically male toys are also more spatial in nature. Legos, Tinker Toys, Lincoln Logs, etc. all have strong spatial components and are or were advertised primarily to males. Furthermore, many current video games feature large-scale virtual environments that require learning new routes and navigating through virtual environments and males play proportionally more video games than females (Terlecki et al., 2008). Thus it could be the case that because males have more experience both mentally rotating objects and using novel solutions, their experiences and abilities are aligned and support the use of novel solutions.

One might expect that if male children are accustomed to using novel solutions, one would see them using them more often. That does not have to be the case though, as familiar solutions also confer advantages such as cognitive offloading. In support of this hypothesis, we do find that males are better than females at novel solutions, but that they are also better than females at all kinds of solutions. This could be because males have accumulated more experience and expertise with using all kinds of navigation solutions, but their experiences and spatial abilities make them particularly well-suited to using novel solutions.

4.6 Is successful navigation the same learning the structure of the environment?

Most previous studies implicitly or explicitly used the assumption that learning a lot about the environment is a marker for how well one will be able to navigate through it. By removing that assumption and directly measuring how successful someone is when they navigate, this study posed the question, *is good environmental learning really the same thing as learning the structure of the environment?* If that is the case, we would expect the same things that predict one's ability to answer questions about the structure of the environment to also predict their ability to successfully navigate through it. This hypothesis was not supported by the data. Measures of preference for solutions and the capacity to use novel solutions have been shown to relate to environmental structure learning (Allen et al., 1996; Hegarty et al., 2004) but were not predictive of successful navigation for all participants. The capacity to use novel solutions was predictive of success in males, but not for females. Furthermore, finding that for females a bias for using familiar solutions and being more flexible in the solutions selected predicts success is inconsistent with previous work on learning the structure of the environment.

This constitutes evidence that learning about the environment is not the same as being able to navigate through it. Thus many previous studies that have been interpreted to relate to successful navigation must be revisited. These studies are not telling an inaccurate story, but rather an incomplete one. Good environmental learning is an important area of interest in itself and it likely does support successful navigation in some individuals or circumstances. But by reducing successful navigation to learning the structure of the environment, we miss out on some of the nuances of what makes us successful. Even worse, this approach may be completely missing the mark on what drives success for females. When one navigates, he/she is under no obligation to use this kind of environmental knowledge. Because navigation is such a complex

and diverse task, it is an oversimplification to reduce it to spatial learning – that is but one component of what it takes to locomote across distances.

4.7 Does volitional solution use relate to required solutions use?

Another open question in spatial cognition is the extent to which the solutions we volitionally use are related to our capacity to use them. Simply put, do we tend to use solutions we are actually good at? This study found no evidence for to support the hypothesis. Neither self-reported preferences nor behaviorally-measures biases were related to an individual's capacity for any kind of solution. On the one hand, this is a somewhat disturbing proposition. It seems downright wasteful that we would not be preferentially using the solutions for which we have the highest capacity. After all, at face value, doing something we are good at should be the simplest way to be more successful when we navigate.

But, this is also an exciting avenue for future work. We do not spontaneously use solutions we are best at, but could we? One possibility is that we simply are not very good at knowing what we're good at. If we end up at our destination eventually, or can resort to using GPS, we may never need to have a thorough understanding of our navigational abilities. This is supported by the mixed evidence for the relationship between subjective preference, which we are aware of, and bias, which we may not be. But perhaps by measuring an individual's abilities and informing them about what they are and are not good at, that individual could more intelligently select solutions for these problems and save themselves time, frustration, and more.

Alternatively, it could be that our biases are more difficult to influence. The ratio of hippocampal activity to caudate activity, which is closely related to the bias for novel versus familiar solutions, respectively, is stable for an individual from encoding through retrieval

(Furman et al., 2014). This could reflect biases in how information is encoded and recalled, which would imply that it would have profound effects on what individuals actually do. Thus the route to improving navigational abilities may be to have individuals understand their implicit biases and help them to improve at the solutions that they are implicitly biased towards. In either case, there is a great possibility that we can improve our navigational abilities by finding a way to more closely align our biases with our capacities.

4.8 Conclusions

Overall, this work provides a picture of what successful navigation is and what it takes for one to be successful. Critically, in contrast to assumptions made by previous research, successful navigation is not the same as learning a lot about the environment. Instead, successful navigation is best understood as a combination of the kinds of solutions one is good at, which are supported by their spatial skills, and the manner in which they select those solutions. Interestingly, males and females differ in terms of the kind of solution capacities that predicts their success. This necessitates a fundamental shift in how we approach navigation and the study thereof.

Much of what we know about navigation, taken from the “good environmental learner” framework, is likely only telling a partial story. By taking the more basic approach of asking, “did you get to your destination?” we are able to get a more rich picture of how one navigates and the factors that separate individuals of different abilities. Understanding these differences also allows for better applications of what we already know about navigation. For example, understanding that the capacity for certain kinds of solutions is critical to successful navigation, and particularly that the critical capacities vary between genders, opens the door for better

matching the information given by navigation devices such as GPS or training regimens to an individual's abilities to increase their future success.

The overarching goal of this work was to shift the dialogue about navigation from what one learns about the environment to whether or not they reach their destination. This goal was driven by the demonstration that learning the structure of an environment is not the same as being successful when navigating through it. By considering navigation in this more holistic fashion, we can gain a more accurate understanding of how humans navigate and more successfully apply this understanding to improving how individuals move around in their daily lives.

References

- Allen, G. (2003). Functional families of spatial abilities: Poor relations and rich prospects. *International Journal of Testing*, 3, 251-262.
- Allen, G., Kirasic, K., Dobson, S., Long, R., & Beck, S. (1996). Predicting environmental learning from spatial abilities: An indirect route. *Intelligence*, 22, 327-355.
- Astur, R., Tropp, J., Sava, S., Constable, R., & Markus, E. (2004). Sex differences and correlations in a virtual Morris water task, a virtual radial arm maze, and mental rotation. *Behavioural brain research*, 151(1), 103-115.
- Baenninger, M., & Newcombe, N. (1989). The role of experience in spatial test performance: A meta-analysis. *Sex roles*, 20(5-6), 327-344.
- Brunyé, T., Taylor, H., & Worboys, M. (2007). Levels of detail in descriptions and depictions of geographic space. *Spatial Cognition and Computation*, 7(3), 227-266.
- Bryant, K. (1982). Personality correlates of sense of direction and geographic orientation. *Journal of personality and social psychology*, 43(6), 1318-1324.
- Carlson, L., Hölscher, C., Shipley, T., & Dalton, R. (2010). Getting lost in buildings. *Current Directions in Psychological Science*, 19(5), 284-289.
- Chase, W. & Chi, M. (1981) Cognitive skill: implications for spatial skill in large scale environments. J. Harvey (Ed.), *Cognition, Social Behavior and the Environment* (111-136), London: Lawrence Erlbaum.
- Clayton, K., & Woodyard, M. (1981). The acquisition and utilization of spatial knowledge. *Cognition, social behavior, and the environment*, 151-161.

- Coluccia, E., Bosco, A., & Brandimonte, M. A. (2007). The role of visuo-spatial working memory in map learning: New findings from a map drawing paradigm. *Psychological research*, 71(3), 359-372.
- Collins, D. W., & Kimura, D. (1997). A large sex difference on a two-dimensional mental rotation task. *Behavioral neuroscience*, 111(4), 845.
- Conte, A., Cornoldi, C., Pazzaglia, F., & Sanavio, S. (1995). The development of the visuo-spatial working memory and its role in spatial memory. *Ricerche di Psicologia*, 19, 95-114.
- Dabbs, J. M., Chang, E. L., Strong, R. A., & Milun, R. (1998). Spatial ability, navigation strategy, and geographic knowledge among men and women. *Evolution and Human Behavior*, 19(2), 89-98.
- Driscoll, I., Hamilton, D. A., Yeo, R. A., Brooks, W. M., & Sutherland, R. J. (2005). Virtual navigation in humans: the impact of age, sex, and hormones on place learning. *Hormones and Behavior*, 47(3), 326–335.
- Fields, A. W., & Shelton, A. L. (2006). Individual skill differences and large-scale environmental learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 32(3), 506-515.
- Furman, A. J., Clements-Stephens, A. M., Marchette, S. A., & Shelton, A. L. (2014). Persistent and stable biases in spatial learning mechanisms predict navigational style. *Cognitive, Affective, & Behavioral Neuroscience*, 14(4), 1375-1391.
- Garden, S., Cornoldi, C., & Logie, R. H. (2002). Visuo-spatial working memory in navigation. *Applied Cognitive Psychology*, 16(1), 35-50.

- Gmeindl, L., Walsh, M., & Courtney, S. M. (2011). Binding serial order to representations in working memory: a spatial/verbal dissociation. *Memory & cognition*, 39(1), 37-46.
- Goodenough, D. R., & Karp, S. A. (1961). Field dependence and intellectual functioning. *The Journal of Abnormal and Social Psychology*, 63(2), 241.
- Granon, S., Vidal, C., Thinus-Blanc, C., Changeux, J. P., & Poucet, B. (1994). Working memory, response selection, and effortful processing in rats with medial prefrontal lesions. *Behavioral neuroscience*, 108(5), 883.
- Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of Personality and Social Psychology*, 74(6), 1464-1480.
- Hegarty, M., Montello, D.R., Richardson, A.E., Ishikawa, T., Lovelace, K. (2006). Spatial abilities at different scales: Individual differences in aptitude-test performance and spatial- layout learning. *Intelligence*, 32(2), 151-176.
- Hegarty, M., Richardson, A.E., Montello, D.R., Lovelace, K., Subbiah, I. (2002). Development of a self-report measure of environmental spatial ability. *Intelligence*, 30(5), 425-447.
- Hegarty, M., & Waller, D. (2004). A dissociation between mental rotation and perspective-taking spatial abilities. *Intelligence*, 32(2), 175-191.
- Hirtle, S. C., & Hudson, J. (1991). Acquisition of spatial knowledge for routes. *Journal of Environmental Psychology*, 11(4), 335-345.
- Iaria, G., Petrides, M., Dagher, A., Pike, B., & Bohbot, V. D. (2003). Cognitive strategies dependent on the hippocampus and caudate nucleus in human navigation: variability and change with practice. *Journal of Neuroscience*, 23(13), 5945–5952.

- Ishikawa, T., & Montello, D.R. (2006). Spatial knowledge acquisition from direct experience in the environment: Individual differences in the development of metric knowledge and the integration of separately learned places. *Cognitive Psychology*, 52(2), 93-129.
- Kaufman, S. B. (2007). Sex differences in mental rotation and spatial visualization ability: Can they be accounted for by differences in working memory capacity?. *Intelligence*, 35(3), 211-223.
- Kosslyn, S. M., Digirolamo, G. J., Thompson, W. L., & Alpert, N. M. (1998). Mental rotation of objects versus hands: neural mechanisms revealed by positron emission tomography. *Psychophysiology*, 35(2), 151-161.
- Kozhevnikov, M., Motes, M.A., Rasch, B., Blajenkova, O. (2006). Perspective-taking vs. mental rotation transformations and how they predict spatial navigation performance. *Applied Cognitive Psychology*, 20(3), 397-417.
- Kozlowski, L. T., & Bryant, K. J. (1977). Sense of direction, spatial orientation, and cognitive maps. *Journal of Experimental Psychology: Human Perception and Performance*, 3(4), 590 – 598.
- Krettek, J. E., & Price, J. L. (1977). The cortical projections of the mediodorsal nucleus and adjacent thalamic nuclei in the rat. *Journal of Comparative Neurology*, 171(2), 157-191.
- Kuhn, T. S. (2012). *The structure of scientific revolutions*. University of Chicago press.
- Lawton, C. A. (1996). Strategies for indoor wayfinding: The role of orientation. *Journal of Environmental Psychology*, 16(2), 137-145.
- Lawton, C.A. (1994). Gender differences in way-finding strategies: Relationship to spatial ability and spatial anxiety. *Sex Roles*, 30(11-12), 765-779.

- Linn, M. C., and Petersen, A. C. (1985). Emergence and characterization of sex differences in spatial ability: A meta-analysis. *Child Development*, 56,1479-1498.
- Linn, M. C., and Petersen, A. C. (1986). A meta-analysis of gender differences in spatial ability: Implications for mathematics and science achievement. In Hyde, J. S., and Linn, M. C. (eds.), *The Psychology of Gender: Advances Through Meta-analysis* (67-101), Baltimore: John Hopkins University Press.
- Lloyd, R. (1989) Cognitive maps: encoding and decoding information. *Annual Association of American Geographers*, 79, 101- 124.
- MacKinnon, D. P., Warsi, G., & Dwyer, J. H. (1995). A simulation study of mediated effect measures. *Multivariate behavioral research*, 30(1), 41-62.
- Marchette, S.A., Bakker, A., Shelton, A.L. (2011). Cognitive Mappers to Creatures of Habit: Differential Engagement of Place and Response Learning Mechanisms Predicts Human Navigational Behavior. *Journal of Neuroscience*, 31(43), 15264-15268.
- Milner, B., Corkin, S., & Teuber, H. L. (1968). Further analysis of the hippocampal amnesic syndrome: 14-year follow-up study of HM. *Neuropsychologia*, 6(3), 215-234.
- Miyake, A., & Shah, P. (1999). *Models of working memory: Mechanisms of active maintenance and executive control*. Cambridge University Press.
- Morris, R. G. (1981). Spatial localization does not require the presence of local cues. *Learning and Motivation*, 12(2), 239–260.
- Neter, J., Wasserman, W. & Kutner, M. H. (1989). *Applied Linear Regression Models*. Homewood, IL: Irwin.
- Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological review*, 84(3), 231-259.

- Parsons, T. D., Larson, P., Kratz, K., Thiebaut, M., Bluestein, B., Buckwalter, J. G., & Rizzo, A. A. (2004). Sex differences in mental rotation and spatial rotation in a virtual environment. *Neuropsychologia*, 42(4), 555-562.
- Pazzaglia, F., & Cornoldi, C. (1999). The role of distinct components of visual-spatial working memory in the processing of texts. *Memory*, 7(1), 19–41.
- Pazzaglia, F., & De Beni, R. (2001). Strategies of processing spatial information in survey and landmark-centred individuals. *European Journal of Cognitive Psychology*, 13(4), 493-508.
- Prestopnik, J. L., & Roskos-Ewoldsen, B. (2000). The relations among wayfinding strategy use, sense of direction, sex, familiarity, and wayfinding ability. *Journal of environmental psychology*, 20(2), 177-191.
- Rogerson, P. A. (2001). Statistical methods for geography. London: Sage.
- Schacter, D. L. (1987). Memory, amnesia, and frontal lobe dysfunction. *Psychobiology*, 15(1), 21-36.
- Schwabe, L., Tegenthoff, M., Höffken, O., & Wolf, O. T. (2010). Concurrent glucocorticoid and noradrenergic activity shifts instrumental behavior from goal-directed to habitual control. *The Journal of Neuroscience*, 30(24), 8190-8196.
- Schwabe, L., Dalm, S., Schächinger, H., & Oitzl, M. S. (2008). Chronic stress modulates the use of spatial and stimulus-response learning strategies in mice and man. *Neurobiology of learning and memory*, 90(3), 495-503.
- Shah, P., & Miyake, A. (1996). The separability of working memory resources for spatial thinking and language processing: an individual differences approach. *Journal of experimental psychology: General*, 125(1), 4.

- Shelton, A. L., & Gabrieli, J. D. (2002). Neural correlates of encoding space from route and survey perspectives. *The Journal of Neuroscience*, 22(7), 2711-2717.
- Shelton, A.L., Marchette, S.A., Brockman, M.J., & Furman, A.J., & (2016). Distinguishing preferences and capacity in human spatial learning profiles. Manuscript in preparation.
- Shelton, A. L., Marchette, S. A., & Furman, A. J. (2013). A mechanistic approach to individual differences in spatial learning, memory, and navigation. *The psychology of learning and motivation*, 59, 223-259.
- Sholl, M. J., Kenny, R. J., & DellaPorta, K. A. (2006). Allocentric-heading recall and its relation to self-reported sense-of-direction. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 32(3), 516.
- Sholl, M. J. (1988). The relation between sense of direction and mental geographic updating. *Intelligence*, 12(3), 299-314.
- Squire, L. (1992). Declarative and nondeclarative memory: Multiple brain systems supporting learning and memory. *Journal of Cognitive Neuroscience*, 4(3), 232-243.
- Taylor, H. A., Naylor, S. J., & Chechile, N. A. (1999). Goal-specific influences on the representation of spatial perspective. *Memory & cognition*, 27(2), 309-319.
- Terlecki M.S., Newcombe N.S. (2005). How important is the digital divide? The relation of computer and videogame usage to gender differences in mental rotation ability. *Sex Roles*, 53, 433–441.
- Terlecki, M. S., Newcombe, N. S., & Little, M. (2008). Durable and generalized effects of spatial experience on mental rotation: Gender differences in growth patterns. *Applied cognitive psychology*, 22(7), 996-1013.

- Thorndyke, P. W., & Hayes-Roth, B. (1982). Differences in spatial knowledge acquired from maps and navigation. *Cognitive psychology*, 14(4), 560-589.
- Vandenberg, S. G., & Kuse, A. R. (1978). Mental rotations, a group test of three-dimensional spatial visualization. *Perceptual and motor skills*, 47(2), 599-604.
- Voyer D., Voyer S., Bryden M.P. (1995). Magnitude of sex differences in spatial abilities: A meta-analysis and consideration of critical variables. *Psychological Bulletin*, 117, 250–270.
- Weisberg, S. M., Schinazi, V. R., Newcombe, N. S., Shipley, T. F., & Epstein, R. A. (2014). Variations in cognitive maps: Understanding individual differences in navigation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 40(3), 669-682.
- Wolbers, T., Hegarty, M. (2010). What determines our navigational abilities? *Trends in Cognitive Sciences*, 14(3), 138-146.
- Zacks, J. M., & Michelon, P. (2005). Transformations of visuospatial images. *Behavioral and Cognitive Neuroscience Reviews*, 4(2), 96-118.
- Zacks, J., Rypma, B., Gabrieli, J. D. E., Tversky, B., & Glover, G. H. (1999). Imagined transformations of bodies: an fMRI investigation. *Neuropsychologia*, 37(9), 1029-1040.

Biographical Sketch

Benjamin Nelligan was born on May 30, 1987 in Evansville, Indiana. He received his undergraduate degree in psychology from Miami University in 2011. During this time, he conducted several lines of research on how reference frame selection under the supervision of Dr. David Waller. He completed his graduate work at Johns Hopkins University under the supervision of Dr. Amy Shelton and Dr. Howard Egeth. This work was aimed at understanding individual differences in how individuals differed in terms of how they navigate and learn about the spatial world around them. This culminated in his dissertation, which used what is known about how individuals differ in how they navigate to better understand which factors influence one's ability to navigate successfully from one location to another. Benjamin is currently a postdoctoral research fellow at the University of Notre Dame and working in Dr. Laura Carlson's spatial cognition lab. His work there continues to explore individual differences in navigation and spatial learning, particularly how situational factors such as stress interact with individual differences.